Trees, Forests and People 14 (2023) 100457

Contents lists available at ScienceDirect

Trees, Forests and People

journal homepage: www.sciencedirect.com/journal/trees-forests-and-people

Climate change impacts: Vegetation shift of broad-leaved and coniferous forests

Rajesh Malla[a,b,*], Prem Raj Neupane[b,c], Michael Köhl[b]

[a] Forest Research and Training Centre (FRTC), Pokhara, Nepal
[b] University of Hamburg, Center for Earth Systems Research and Sustainability (CEN) & IWS-World Forestry, Germany
[c] Friends of Nature, Nepal (FON), Kathmandu 44618, Nepal

ARTICLE INFO

Keywords:
Climate change
Broad-leaved
Coniferous
Forest
MaxEnt
Model
Nepal

ABSTRACT

Climate change is a variation in temperature and precipitation for longer periods due to global warming. It has an impact on tree species distribution, composition and diversity of the forests. Our study aims to answer how future climate change is likely to have an impact on the vegetation shift of broad-leaved and coniferous forests. The study used forest resource assessment data (2010–2014) of Nepal to assess vegetation shift from the perspective of climate change scenario. We collected altogether 392 presence points (observations) for broad-leaved forests and 99 for coniferous forests. These occurrence points accompanied by bioclimatic variables and topographical variables (Elevation, Slope and Aspect) were used as input data in a MaxEnt model to predict the distribution of the coniferous and broad-leaved forests. We found a potential area of the near current (1970–2000) coniferous forest replaced by a broad-leaved forest under a climate change scenario (SSP2 4.5 for 2041–2060) and vice versa. The total projected vegetation shift area of Nepal was found to be approximately 1800 km^2 (i.e. over 3 % of the total forest area). Out of the total vegetation shift area, almost 90 % percent of the area was found to be replaced by broad-leaved forest while the remaining 10 % area was found to be replaced by a coniferous forest. The climate change impact has been noticed in the vegetation shift, particularly the presence of broad-leaved forest is more dominant. The study provides better insights into the impact of climate change on the existing vegetation under the future climate change scenario.

1. Introduction

Climate change, a variation in temperature and precipitation regimes, persists for a long period (IPCC, 2013). The global average temperature has increased by 1.1 °C from the period 1850–1900 to 2011–2020(IPCC, 2023) whereas per decade increase of global warming in all the continents has been reported to raise by 0.13 °C during the past 50 years from the period 1948–1998 (Pepin and Seidel, 2005) and the rate is supposed to increase by 0.25–0.48 °C/decade until 2085 (Nogués-Bravo et al., 2007). At the country level, Nepal's warming rate is 0.056 °C/year, with the highest rate of increase in higher altitudes (GoN/MoFE, 2021). The Himalayan region has been reported to have a warming rate approximately 3 times higher than the global average (Xu et al., 2009).

Forest ecosystems are sensitive to climate change and experience changes such as changes in species abundance, forest types, growth rate, structure of forests, tree mortality and tree vitality (Bhatta et al., 2021; Gebeyehu, 2019; Heidenreich and Seidel, 2022; Keane et al., 2020; Kelly and Goulden, 2008b; Taccoen et al., 2022; Thapa and St. George, 2019; Trisurat et al., 2009). Climate change has both positive and negative impacts on forests. Increase in the growth of conifer forests (Wu et al., 2019), an increase in wood production and carbon stock (EGGERS et al., 2008), and an increase in species richness (Zhou et al., 2013) are examples of positive impacts while depletion of the highland ecosystem (Manish et al., 2016), habitat shrinkage of medicinal and aromatic plants (MAPs)(Shrestha et al., 2022) and threatened conifers (Xie et al., 2022), increasing infestation of pest and invasive species (Gebeyehu, 2019) are examples of negative impacts. Climate change studies in Nepal are focused on invasive alien species (Shrestha et al., 2018; Shrestha and Shrestha, 2019; Siwakoti et al., 2016), biodiversity and ecosystem (Bhattacharjee et al., 2017; Paudel et al., 2021; Thapa et al., 2013), medicinal and aromatic plants (Rana et al., 2020; Shrestha et al., 2022), freshwater ecosystems (Lamsal et al., 2017; Singh et al., 2022), human-wildlife- ecosystems interaction (Aryal et al., 2014), and

* Corresponding author.
E-mail address: raj_malla@yahoo.com (R. Malla).

https://doi.org/10.1016/j.tfp.2023.100457

Available online 7 November 2023

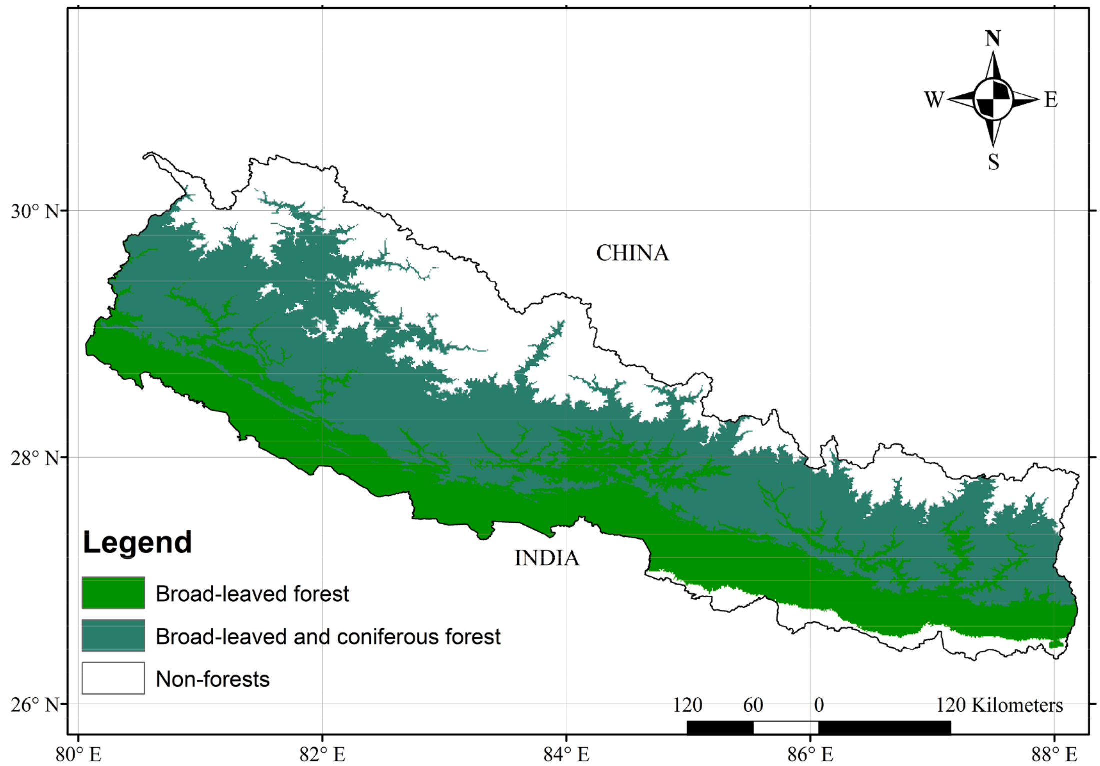

Fig. 1. Map of Nepal showing the distribution of broad leaved and coniferous forests based on the permanent sample plots of forest resource assessment (2010–2014).

Table 1
Forest types information of Nepal.

S. N	Forest types	Altitudinal range (m)	Temperature (°C) (1970–2000)[a]	Precipitation (mm) (1970–2000)	Main dominant tree species	Remarks
1	Coniferous forest	869–3600	−2.7 – 20.5	351 - 2273	*Pinus roxburghii, Pinus wallichiana, Pinus patuala*	Conifers represent more than 60 % of the basal area (DFRS, 2015)
2	Broad-leaved forest	88–3587	2.9 – 24.7	388 - 3215	*Shorea robusta, Castanopsis indica, Schima wallichi, Quercus sps, Rhododendron sps*	Broad-leaved species represent more than 60 % basal area

[a] Mean annual temperature and Annual precipitation from the period of 1970–2000 accessed from www.worldclim.org on 10 June 2022.

Table 2
Environmental variables used in MaxEnt modeling.

Source	Category	Variable description	Unit
United States Geological Survey (USGS)	Topographic	Elev - Elevation	m
		Slp - Slope	Degree
		Asp – Aspect	Degree
World climate	Climatic variable	BIO2 - Mean Diurnal Range (Mean of monthly (max temp - min temp))	°C
		BIO3 - Isothermality (BIO2/ BIO7) (×100)	°C
		BIO9 - Mean Temperature of Driest Quarter	°C
		BIO12 - Annual Precipitation	mm
		BIO14 - Precipitation of Driest Month	mm
		BIO15 - Precipitation Seasonality (Coefficient of Variation)	mm
		BIO19 - Precipitation of Coldest Quarter	mm

habitat distribution (Baral et al., 2023; Chhetri et al., 2018; Rai et al., 2022) .

Climate change is causing an expansion of broad-leaved deciduous tree distribution in the boreal forests (Thuiller et al., 2006) suggesting a vegetation shift from coniferous-dominated forests towards broad-leaved species (Hufnagel and Garamvölgyi, 2014; Lindner et al., 2010; Xiao-Ying et al., 2013). In contrast, higher-elevation broad-leaved forest is invaded by lower-elevation coniferous forest in response to climate change (Bai et al., 2011). Both pieces of evidences show a vegetation shift due to climate change taking place in both directions (i.e. Broad-leaved to coniferous and its reverse). The causes of vegetation shift are due to change in the threshold range of the climatic variables, particularly, mean annual precipitation (Zhao et al., 2017), change in climatic variability, particularly drought accompanied by stand structure and topography (Rigling et al., 2013) and increase in CO^2 emission, temperature and precipitation (Hufnagel and Garamvölgyi, 2014).

Climate is considered as a major determinant of forest distribution (Kelly and Goulden, 2008a; Lenoir et al., 2010). In Nepal, the broad-leaved forests are more likely to occur in high -rainfall areas, whereas coniferous forests are confined to low rainfall areas (Bhatta et al., 2021). Presence of broad-leaved forest and coniferous forest under different site conditions, it is important to know the potential impact of future climate change on the adaptive capacity of natural tree vegetation (coniferous and broadleaved forest). Therefore, this study was conducted by combining observational data and model-based approach options to determine the current potential distribution of broad-leaved and coniferous forests and their vegetation shift under future climate

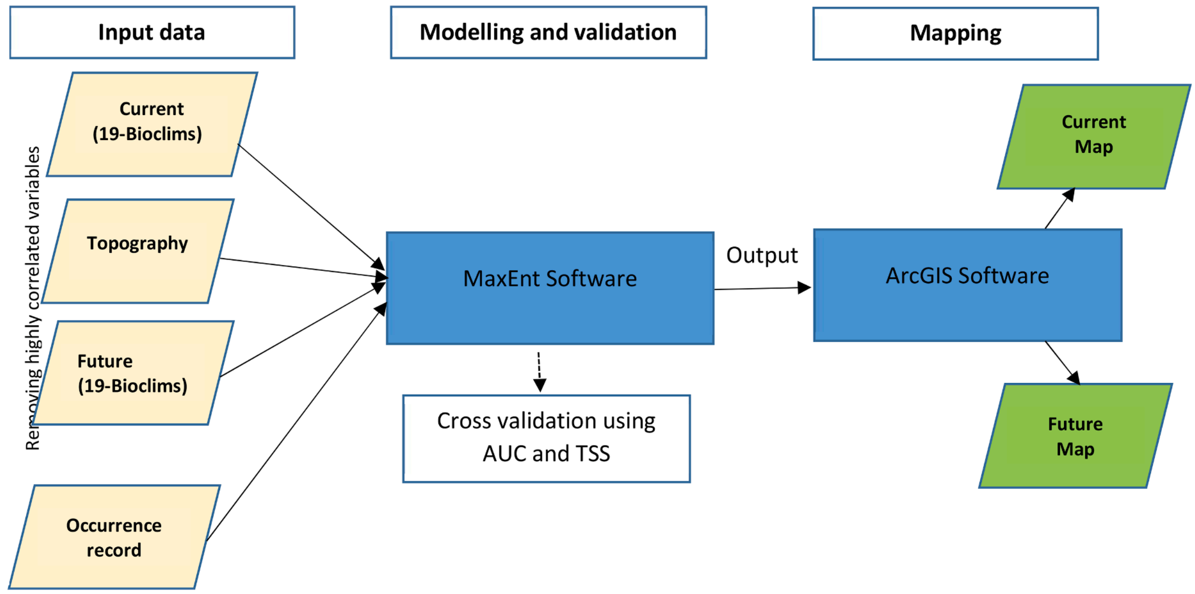

Fig. 2. Flowchart of the methodology used in the MaxEnt modeling and mapping in Arc GIS.

change scenarios. The overarching objective of this study was to explore how broad-leaved and coniferous forests respond to climate change from the perspective of vegetation shift under future climate change scenarios. The study covers all the forest areas of Nepal and intends to improve our understanding of climate change impact on vegetation shift.

2. Methods

2.1. Study area

We conducted this study in Nepal - known as a Himalayan country (latitude 28.3949^{0}N & Longitude 84.1240^0 E) – that lies between India and China with diverse forest types due to its altitudinal and climatic variations. Stainton (1972) has identified 35 forest types and further grouped them into ten major types[1] based on elevation and species. The distribution of broad-leaved forests occur from the lower region to high mountain region, whereas the coniferous forests are mostly confined to the middle mountain and high mountain regions (DFRS, 2015b, DFRS, 2015a). With the increase in altitude, coniferous forests are replacing broad-leaved forests. The distribution of coniferous forest occurs only in the altitudinal range of 869 m to 3600 m, whereas broadleaved forest occurs throughout the range (Fig. 1). We grouped the forests found in this range into two categories, i.e. coniferous forest and broad-leaved forest (Table 1). The habitats and characteristics of the major forest types within these groups are briefly described below:

2.2. Modeling and mapping

We intended to assess spatial distribution and vegetation shift of coniferous and broad-leaved forest in the future climate change scenario. The potential distribution of the floral and faunal species has been done by using Maximum-entropy (MaxEnt) model in Nepal (Gajurel et al., 2014; Mahatara et al., 2021; Rai et al., 2022; Su et al., 2021). The MaxEnt model, a machine learning algorithm, has been widely used to predict the potential distribution of species [70–72] and also considered a highly performant species distribution modeling algorithm (Elith et al., 2006; Fyllas et al., 2022; Grimmett et al., 2020). We used this model for assessing the potential distribution of the coniferous and broad-leaved forests under future climate change scenarios to better understand climate change impact on vegetation shift.

As an input variable for the model, we used presence points (latitude and longitude) of the forests, topographic variables and climatic variables (projected) which gives distribution map of the forest along with variable response curves in the future climate change scenario as an output. The model used known points and predictor variables to estimate the probability of presence points throughout the study area. We extracted 49 presence points (observations) for coniferous forests and 392 for broad-leaved forests from the forest resource assessment (2010–2014) data of Nepal. In addition, 114 presence points for coniferous forests were extracted from secondary sources (study reports, forest mapping work and visual interpretation) to increase sample points in the study.

We applied a spatial filter of ~1 km x 1 km grid size to maintain at least 1 km distance among the presence points for reducing autocorrelation (Fortin, 1999). Thus, 392 presence points for broad-leaved and 99 presence points for coniferous points were used in this study. Similarly, we downloaded freely available topographical variables (altitude, slope and aspect) from United States Geological Survey (USGS)[2] and pre-processed them in ArcGIS (ESRI, 2017) to prepare in the required format (ASCII), extent, and spatial resolution (30 m).

Moreover, a relatively high resolution of climatic data is appropriate for the area with a diverse climate at a short distance. Therefore, 19 bioclimatic variables (current and projected) were downloaded from world climate data[3] at 30 ′ (~1 km^2). A multicollinearity analysis was performed to remove highly correlated variables (r > 0.7) to improve the prediction of the model using *vifstep* function under "usdm" package in R program (Naimi et al., 2023) and remaining 7 bioclimatic variables (Bio2, Bio3, Bio9, Bio12, Bio14, Bio15 and Bio19) were used for the modeling (Table 2). The *vifstep* function calculates the variance inflation factor of a set of predictor variables and excludes highly correlated variables through a stepwise procedure. For the prediction of the

[1] Tropical forest (<1000m), Subtropical broad-leaved forest (1000-2000m), Subtropical pine forest (1000-2200m), Lower temperate broad-leaved forest (1700-2700m), Lower temperate mixed broad-leaved forest (1700-2200m), Upper temperate broad-leaved forest (2200-3000m), Upper temperate mixed broad-leaved forest (2500-3500m), Temperate coniferous forest (2000-3500m), Sub-alpine forest (3000-4100m), Alpine scrub (>4100m)

[2] www.usgs.gov

[3] www.worldclim.org

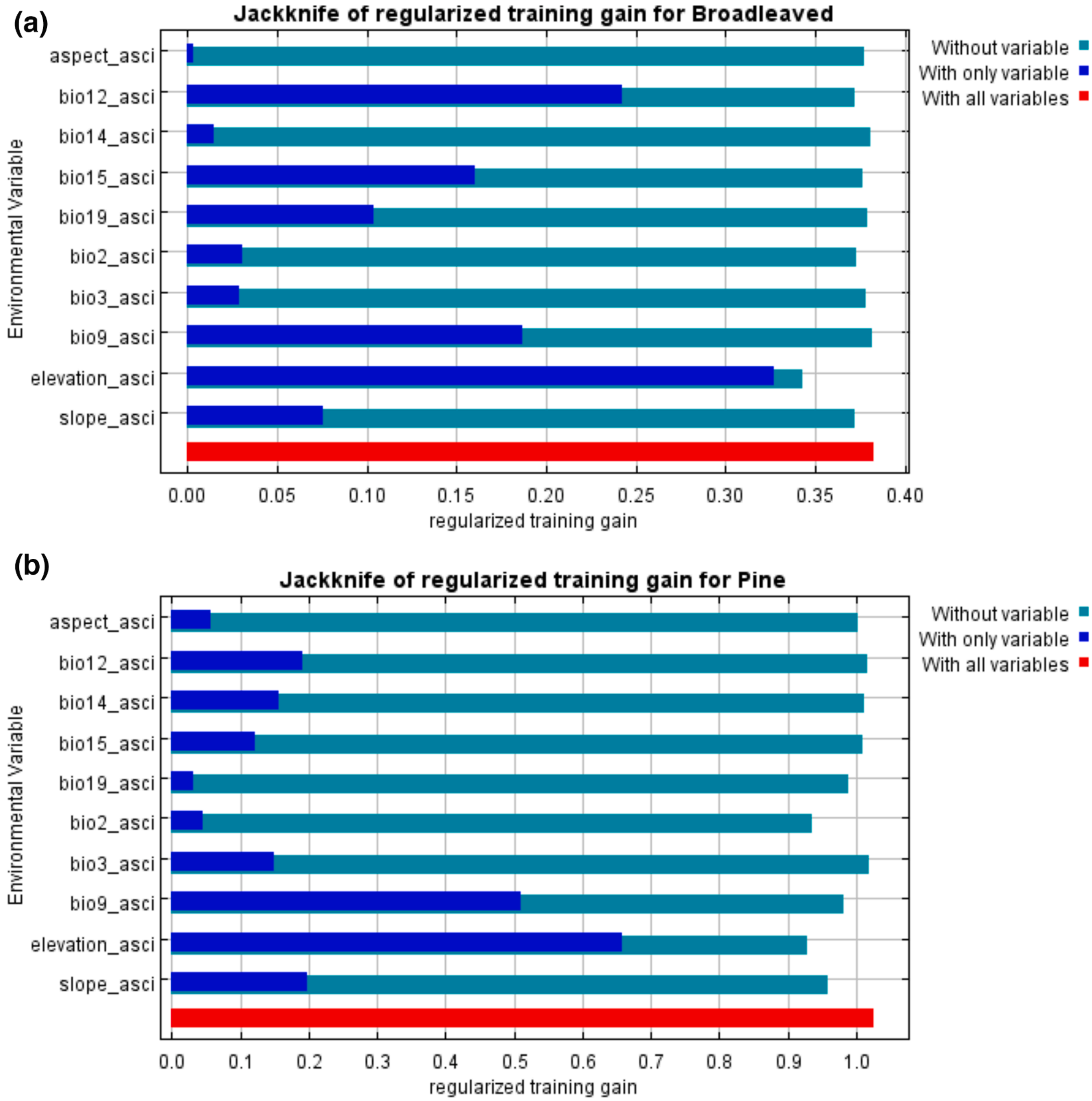

Fig. 3. A Jackknife test of variable importance (regularized training gain) for modeling broad-leaved (a) and coniferous (b) forest distribution based on ten predictor variables.

potential distribution of the broad-leaved and coniferous forests, we used 7 projected bioclimatic variables from MIROC6/GCMs (Global climate models) model under Shared Socio–economic Pathways (SSP2 4.5) scenario for the period of 2041 to 2060 (average 2050).

To run the MaxEnt model in our study, the occurrence points of the forests were examined as a response variable while bioclimatic variables, altitude, slope and aspect as the predictor variables. The model is also used for predicting the distribution of the species in Nepal (Gajurel et al., 2014; Mahatara et al., 2021; Rai et al., 2022; Su et al., 2021). We used 10 replicates (ran the model 10 times) and 1000 background points (points that represent environments or features of the study area) in the model for the prediction (Barbet-Massin et al., 2012) in our study.

The distributions of coniferous and broad-leaved forests in the near current period (1970–2000) and future climate change scenarios (2041–2060) were identified by the MaxEnt software and for further analysis (change in area and spatial distribution) and mapping Arc GIS software was used. We followed steps of building model, its validation and finally preparing map as an output (Fig. 2).

2.3. Accuracy assessment of the models

Accuracy assessment is an important step in the process of developing models that helps validate and evaluate the performance of the model. The 70 % of the occurrence points of broad-leaved and coniferous forests were allocated for the training dataset to develop the models. The remaining 30 % occurrence points were allocated for validating the models. We used two methods to evaluate namely Area under the receiver-operator curve (AUC) which is threshold independent, and True Skill Statistics (TSS) which is threshold dependent. The AUC of models was obtained directly from the model (Phillips et al., 2006; Wiley et al., 2003). Its value, i.e. <0.7, 0.7–0.9 and >0.9, denotes poor model performance, moderately useful model performance, and excellent model performance respectively (Pearce and Ferrier, 2000). Although AUC is a classical and widely used model evaluation parameter, it is criticized by researchers (Lobo et al., 2008). Therefore, in addition, TSS was calculated for the model evaluation (Merow et al., 2013). The value of TSS ranges from -1 to 1, where a value < 0 indicates

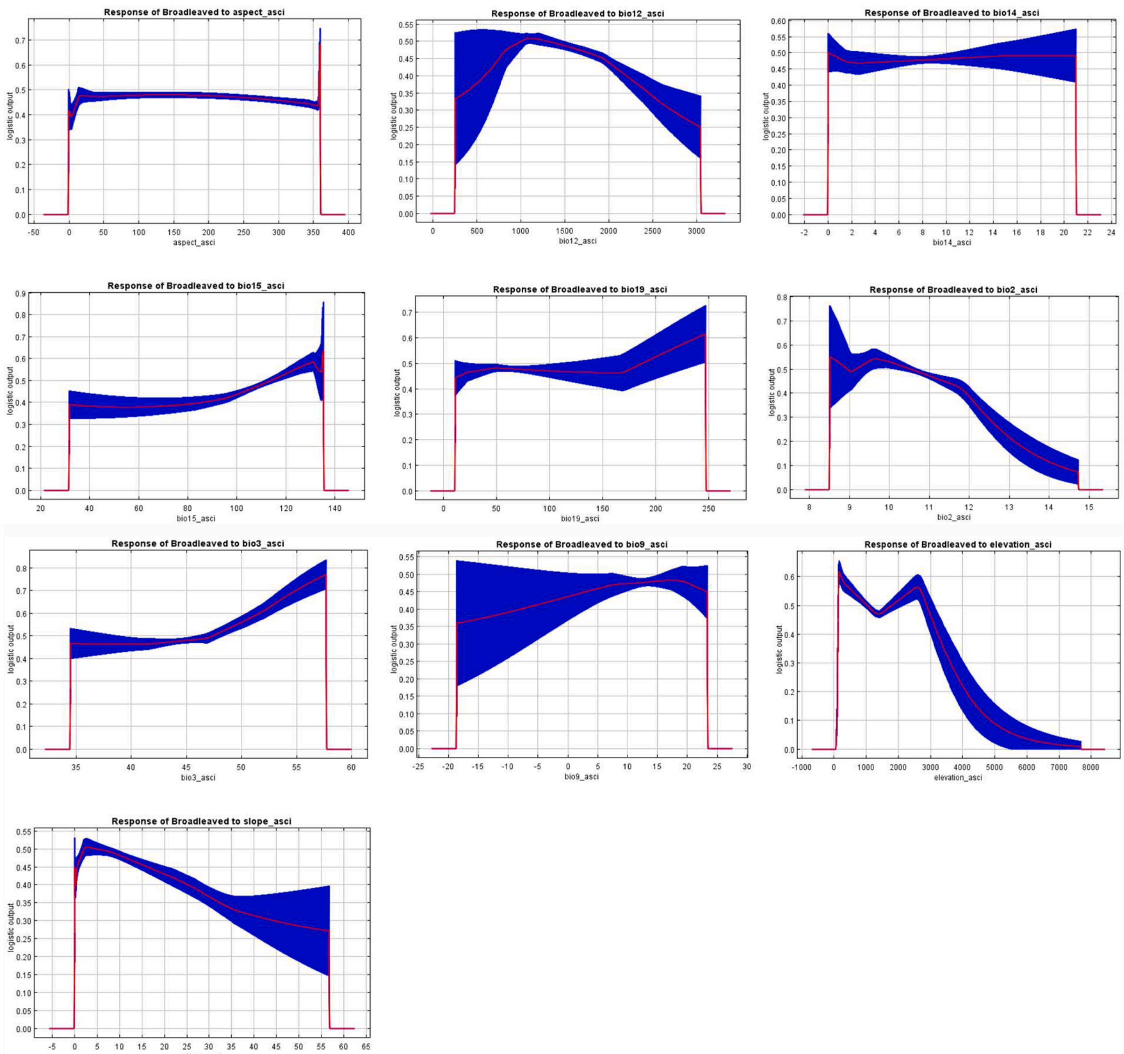

Fig. 4. Response curve of seven bioclimatic and three topographic predictor variables for the distribution of broad-leaved forests. X –axis represents predictor variables, Y- axis represents occurrence probability. Red line represents mean of occurrence probabilities of a predictor variable whereas blue color represents a range of occurrence probability of the predictor variable.

a performance no better than random and 1 indicates a perfect fit of the model (Allouche et al., 2006). TSS was calculated for all model outputs (10 replications), and the final TSS was the average of all 10 replications for coniferous and broad-leaved forests.

3. Results

3.1. *Model performance and contribution of predictor variables in the model*

The MaxEnt model used in our study shows a better distribution of the coniferous forest at near current period (1970–2000) and in the future climate change scenario (2041–2060) than broad-leaved forests. The AUC and TSS of the model for coniferous forests was found to be 0.840 and 0.551 respectively, while for the broad-leaved forests it was 0.698 and 0.311 respectively. According to the relative percent contribution (gain in model when variable is added) of the ten predictor variables, annual precipitation (Bio12) and elevation were the most influential variables in the distribution of both broad-leaved and coniferous forests (Annex1).

Similarly, Fig. 3 shows the variables contribution to the model based on the Jackknife test. The Jackknife test reveals the contribution of the predictor variables on shuffling randomly to observe the effect on the model accuracy (permutation-based importance). Elevation, Mean Temperature of Driest Quarter (Bio9) and Annual precipitation (Bio12) were predictor variables for the distribution of both coniferous and broad-leaved forests while Precipitation Seasonality (Bio15) for broad-leaved forest and Precipitation of Driest Month (Bio14) for coniferous forests.

The result shows that all the predictor variables contributed to the gain of the model. The highest gain of the model by the predictor variable was the "elevation" in both the forests types. It means that when elevation is omitted, it decreases the gain most in the model (Fig. 3).

3.2. *Variables response curve*

The variable response curves of the ten influential variables for the distribution of broad-leaved and coniferous forests are shown in Figs. 4 and 5, respectively. These curves depict how a specific variable responds in the occurrence of the species, while other variables remain unchanged. A response curve with one predictor variable shows the optimal environmental condition that represents the distribution of both forests. The optimal range for example of Annual precipitation (Bio12) i.e.1000–2000 mm, elevation i.e. <1000 m and 2000–3000 m, Mean Diurnal Range (Bio2) –i.e. 8–9 °C was found for the distribution of broad-leaved forests (Fig. 4) whereas the optimal range of Annual

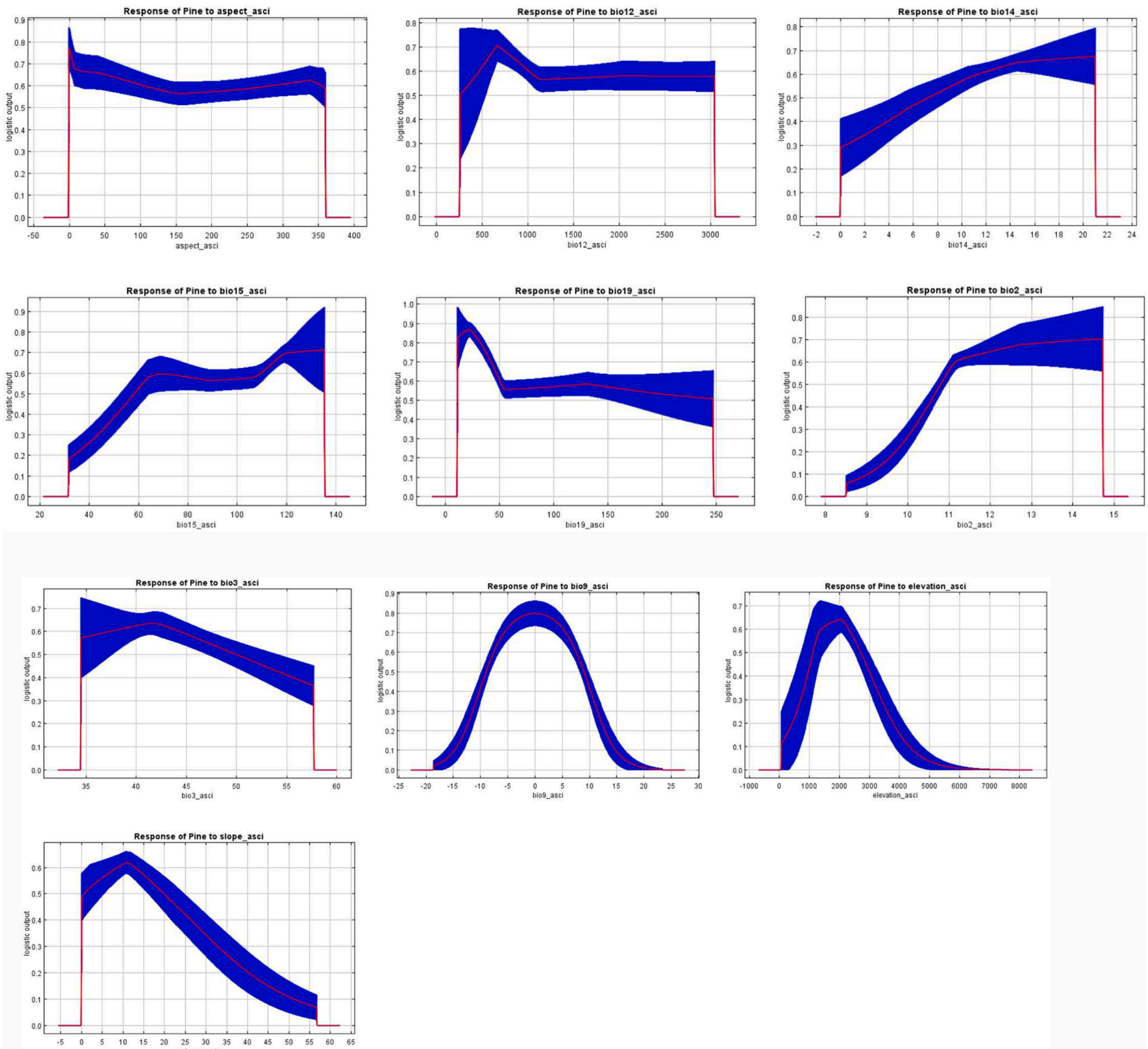

Fig. 5. Response curve of seven bioclimatic and three topographic predictor variables for the distribution of coniferous forests. X –axis represents predictor variables, Y- axis represents occurrence probability. Red line represents mean of occurrence probabilities of a predictor variable whereas blue color represents a range of occurrence probability of the predictor variable.

precipitation (Bio12) i.e.250–750 mm, Elevation i.e. 1000–2000 m and Mean Diurnal Range (Bio2) i.e. 12–14.5 °C was found for coniferous forests (Fig. 5)

3.3. Distribution of broad-leaved and coniferous forests

The current distribution of the broad-leaved forests and their future distribution under the climate change scenario (2041–2060) show that these forests are likely to occupy most of the area of Nepal (Fig. 6) in the upcoming decades. In the near current period, the potential distribution of the broad-leaved forests was found to be approximately 90,000 km^2, while its distribution increased by 912 km^2 in the future climate change scenario (Table 4). The result shows that the distribution of broad-leaved forests was found to shift 77 m upwards in higher altitudes (i.e. 3767 m to 3844 m altitude) while no lower shift from the lowest altitude in the future climate change scenario (Table 5).

The distribution of the coniferous forest under the future climate change scenario forests is likely to decrease (Fig. 7). In the near current period, total potential area of the coniferous forest was found to be 43,075.3 km^2 while the area is likely to decrease by 18,020.4 km^2 in the future climate change scenario (Table 3). The result shows that the distribution of coniferous forests was found to shift 54 m lower at the higher altitude (i.e. 4928 m to 4874 m) whereas 214 m higher at lower altitude (i.e. 796 m to 1010 m) in the future climate change scenario (Table 4). Potential area of the coniferous forests distributed in the lower region is likely to decrease more than the higher region in the future climate change scenario (Fig. 7b). It shows that climate change influences habitat shrinkage of coniferous forests occurring in the lower and higher elevation.

3.4. Climate change impact on vegetation shift

We found an area of coniferous forests near the current period would be shifted into a broad- leaved forest under the climate change scenario and vice versa. The total vegetation shift area was found to be 1810 km^2 which is more than 3 % of the total forest area of Nepal (Table 5). Out of the total vegetation shift area, almost 90 % percent of the shifted area would be occupied by broad-leaved forests replacing coniferous forests while the remaining 10 % of the area would be occupied by coniferous forests replacing broad-leaved forests (Fig. 8). The vegetation shift of coniferous forests into broad-leaved forests is more dominant than the broad-leaved into coniferous forests under future climate change

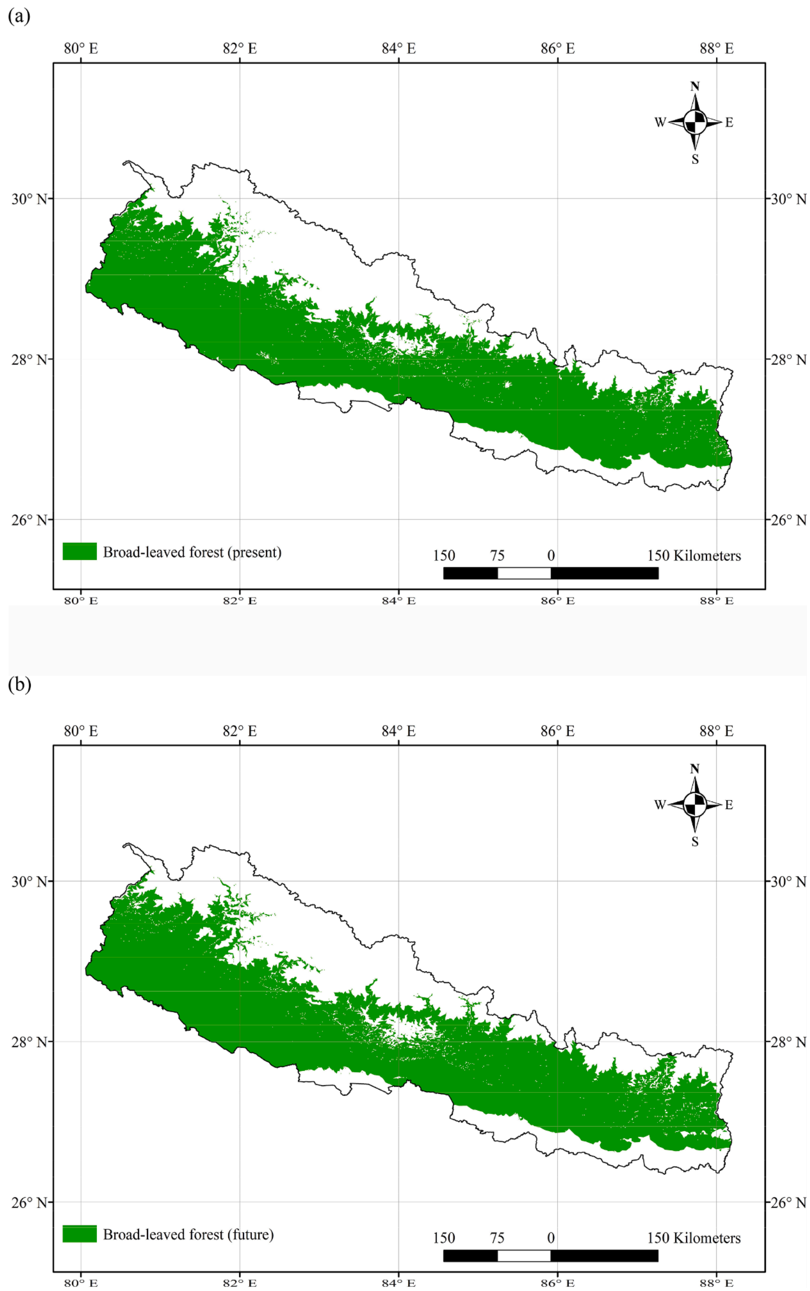

Fig. 6. Potential distribution of the broad-leaved forest at near current (a) and in the future (b).

scenarios. The result shows that climate change is likely to cause a vegetation shift in the future.

4. Discussion

The result shows that coniferous forests are more likely to shift into broad-leaved forest in the future (Fig. 8a), supporting the hypothesis of climate change impact on the vegetation shift, i.e. one vegetation into another In agreement with our study of coniferous forests, (Fyllas et al., 2022) reports that climate change leads to potential habitat shrinkage of the species in the higher elevation. Previous studies also reported the impact of climate change on species composition (Feeley et al., 2011), the upward shift of species (Li et al., 2020; Parmesan and Yohe, 2003), and increasing/decreasing species richness (Adhikari et al., 2018; Zhou et al., 2013). Moreover, human disturbance (i.e., tree harvest) contributes to future species distribution along with climate change (Wang et al., 2019).

The distribution of the broad-leaved forest and the coniferous forest is largely determined by annual precipitation (Bio12) and elevation. Elevation and the annual mean temperature (Bio1) are highly correlated and thus elevation can be used as a proxy for climatic variables (Hanawalt and Wittaker, 1976; Malla et al., 2022). Climatic variability is considered a major driver of vegetation shift. The findings of vegetation shift (broad-leaved to coniferous or vice versa) due to climate change in our study are supported by other studies (Hiura et al., 2019; Rigling et al., 2013; Tian and Fu, 2020). Climatic variables (Temperature and precipitation) are important factors in tree and forest growth (Toledo et al., 2011) However, seasonal temperature and precipitation determine the growth of a tree which is species-specific (Gauli et al., 2022) showing that different tree species respond differently with the changing climate. Forests are sensitive to climate change, thus the spatial distribution of broad-leaved forest and coniferous forest has increased over the past 3 decades but at a different rate (Tian and Fu, 2020)

The spatial distribution of broad-leaved and coniferous forests is

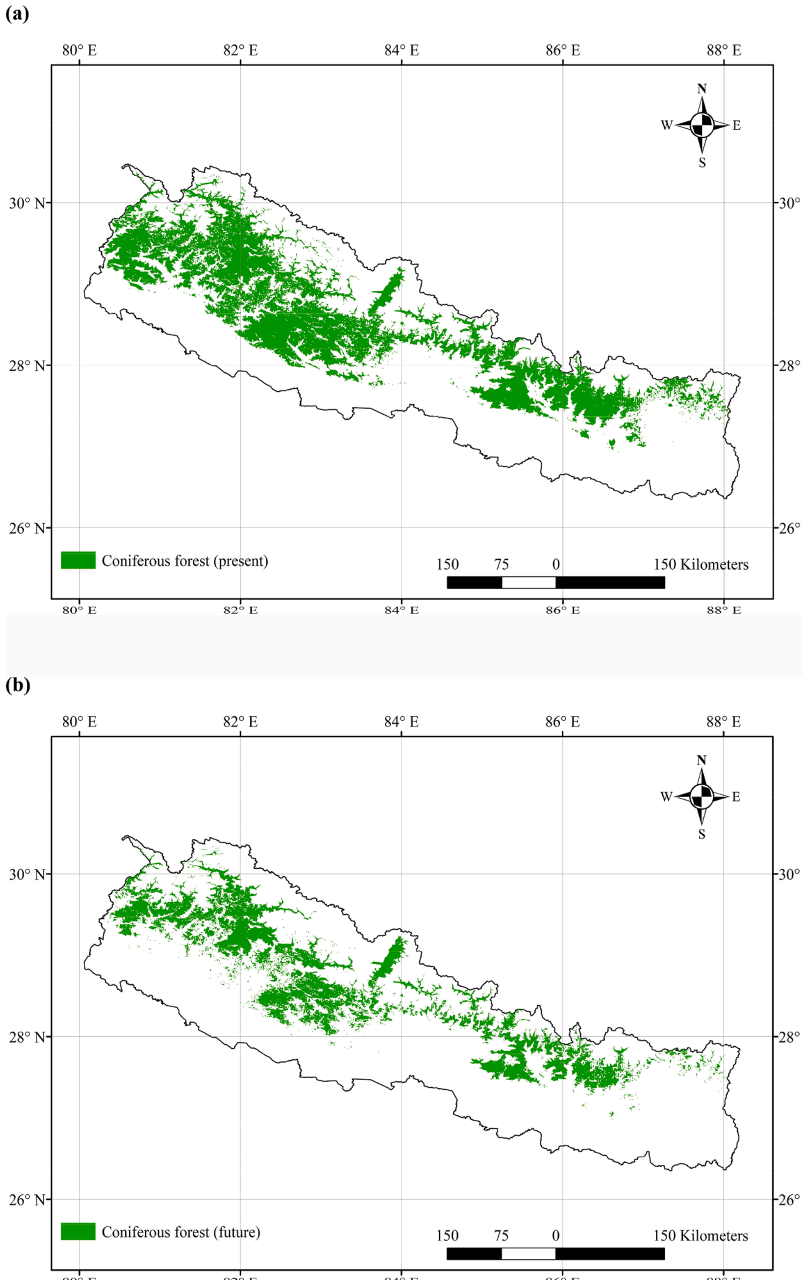

Fig. 7. Potential current (a) and future (b) distribution of coniferous forest.

Table 3
Change of forests area under climate change scenario (2041–2060).

SN	Forests	Suitable areas (km^2)		Change (km^2)
		Near current	Future	
1	Broad-leaved	89,667.09	90,579.17	912.08
2	Coniferous	43,075.3	25,054.9	-18,020.4

different in Nepal. The broad-leaved forests occupy most of the area of the forests compared to coniferous forests. Further, the coniferous forests are confined to the low precipitation area while the broad-leaved forest receives high precipitation (Bhatta et al., 2021) which shows that low precipitation favors coniferous forests more than the broad-leaved forest. In the future climate change scenario (SSP2 4.5 scenario for 2041–2060), the amount of precipitation increases (from 1351.69 mm at the near current to 1418.88 mm in 2041–2060) which could lead to an increased spatial distribution of the broad-leaved forest. Particularly, human-induced global warming acts as a driving factor to increase the frequency, intensity and amount of precipitation (IPCC, 2018)

Table 4
Potential distribution of broad-leaved and coniferous forest at near current (1970–2000) and in the future climate change scenario (2041–2060) with varying altitudinal ranges.

Forest	Current elevation (m)			Future elevation (m)		
	Min	Mean	Max	Min	Mean	Max
Pine	796	2836.93 (1056.58)	4928	1010	2774.67 (933.37)	4874
Broad-leaved	117	1804.32 (976.61)	3767	117	1841.91 (997.23)	3844

Note: Standard deviation shown in parenthesis.

Table 5
Vegetation shift (broad-leaved to coniferous forest and its reverse) in climate change scenario (SSP2 4.5 for 2041–2060.

S.N	Vegetation shift	Area (km^2)	Percentage
1	Coniferous forests into Broad-leaved forests	1578.82	87.19
2	Broad-leaved forests into Coniferous forests	231.90	12.81
	Total	**1810.72**	**100**

Similarly, the temperature increase in future climate change scenarios (from 14.05 °C at the near current to 15.47 °C in 2041–2060) is supposed to favor the expansion of broad-leaved forests. The emission of greenhouse gases due to anthropogenic activities such as burning fossil fuel and forest fires are the main reason to increase global temperature (IPCC, 2018). The lower regions of Nepal are covered mostly with broad-leaved forests (Fig. 6a). Particularly, the increase in temperature is more pronounced in higher altitudes of Nepal (GoN/MoFE, 2021) which supports our findings in the future scenarios, i.e. the upward shift of broad-leaved forests. The change in vegetation shift and geographical distribution may have several possible reasons, but more specifically, it is due to climate change (Parmesan and Yohe, 2003).

The projected vegetation shift in the future climate change scenario will have implications on forest dynamics and the livelihoods of the coniferous forests dependent people. An increasing area of broad-leaved forest in the future climate change scenario leads to an increase in species diversity (Joshi et al., 2022) and an increase in soil organic carbon (Chiti et al., 2012; Joshi et al., 2022) which helps make these forests climate resilient. On the other hand, people dependent on the coniferous forests are likely to be more vulnerable.

Moreover, the MaxEnt model predicts potential distribution of existing vegetation in the study area based on the input data. Potential area of a particular foret vegetation given by the MaxEnt model does not mean that the vegetation exists there but there might be other vegetation or biomes at present. The existing and potential areas of the

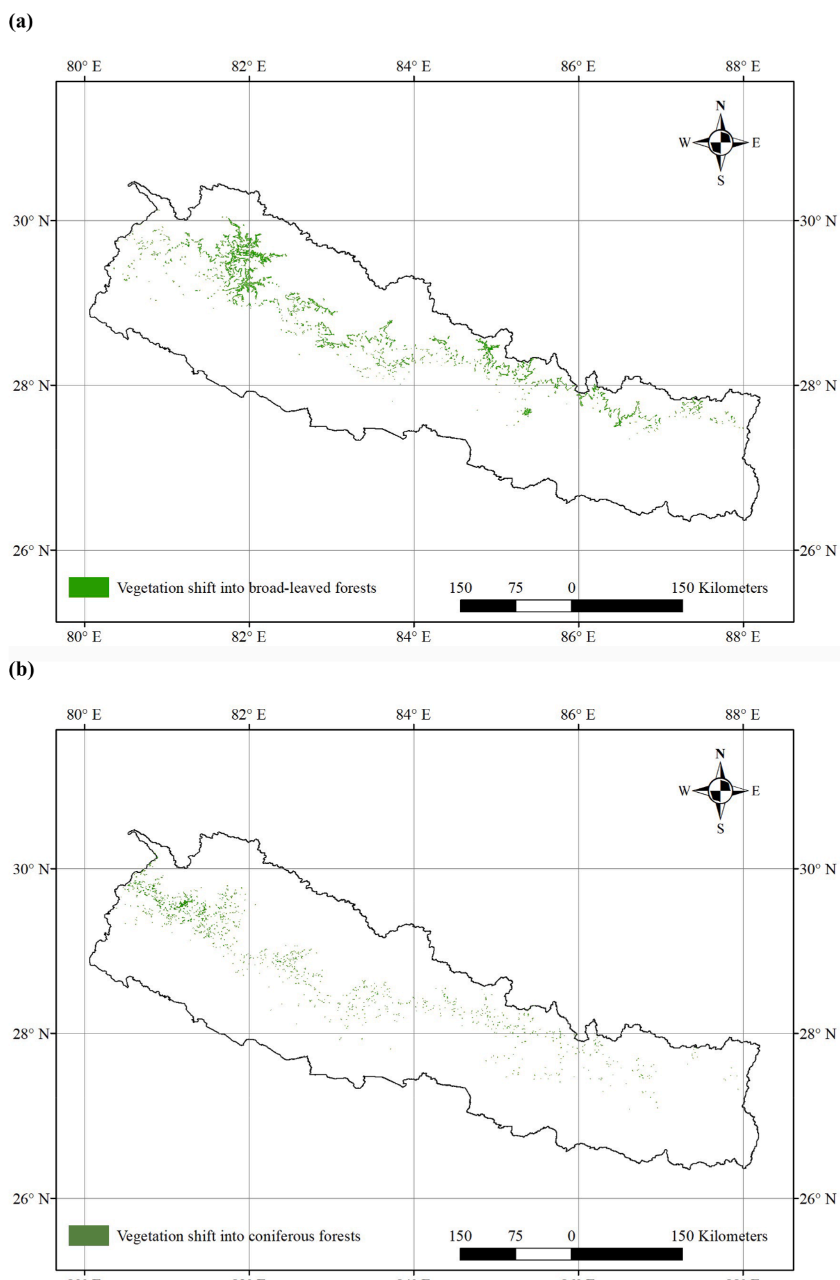

Fig. 8. Vegetation shift from coniferous into broad-leaved (a) and Vegetation shift from broad-leaved into coniferous (b) under climate change scenario.

particular vegetation under study share common environmental conditions which is a basis to predict species distribution. However, negative impact of climate change, such as increased number of fire incidences (Mishra et al., 2023), invasive alien plant species (Shrestha et al., 2018; Shrestha and Shrestha, 2019) and forest pests outbreaks (Pureswaran et al., 2018) accompanied by human disturbances may hinder the vegetation shift differently than the speculation of this study. This study does not provide information on how the transition of forests takes place during the entire process and how climate-induced severe events (forest fire, forest pests/disease, and invasive alien species) and human disturbances affect the vegetation shift process. Depending on the time course of climate change, vegetation shift can occur either abruptly through large-scale mortality events or gently through gradual changes in species abundance. The support of adaptation processes by human intervention must take into account site changes and corresponding changes in potential natural tree vegetation. Especially with the onset of reduced tree vitality and tree mortality, measures for the conservation of current trees or restoration of past species abundances should be critically evaluated based on future potential natural tree species vegetation. Further study on vegetation shift requires climate-induced severe events and human disturbances along with climatic variables for a better understanding the vegetation shift process under climate change scenarios.

5. Conclusion

Climate change in the future scenario shows its impact on the vegetation shift of broad-leaved forests to coniferous forests and vice-versa. However, the vegetation shift from coniferous forest to broad-leaved forest is seen as more dominant. The impact of climate change is not only limited to the area of forest change but is also seen in the altitudinal shift of the newly formed forests. As a result of vegetation shift, it may affect the accumulation of soil organic carbon (SOC), species diversity, and climate resilient capacity of the forest. Vegetation shift to broad-leaved forests under climate change scenario could benefit in terms of maintaining species diversity, and providing multiple-use products and eco-system services. Similarly, vegetation shift from coniferous to broad-leaved forest may negatively affect the coniferous forest dependent local people and forest based enterprises by losing the benefits from the forests in the future.

Availability of data and materials

Data that supports the findings of this study are available from Forest Research and Training Center (FRTC), Kathmandu, Nepal but not publicly accessed due to the data sharing protocol of the FRTC. However, data can be obtained by following formal process of written application with supporting documents.

Declaration of Competing Interest

The authors declare that they have no competing interests.

Data availability

Data will be made available on request.

Funding

This research was partially funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany’s Excellence Strategy—EXC 2037 ’CLICCS—Climate, Climatic Change, and Society’—Project Number: 390683824, contribution to the Center for Earth System Research and Sustainability (CEN) of Universität Hamburg.

Acknowledgements

The Authors are thankful to FRTC, Kathmandu for the provision of data and to the reviewers for their constructive comments and suggestions.

Annex1

Relative percent contribution of the predictor variables in the MaxEnt model.

S.N	Variable	Abbreviation	Relative percent contribution	
			Broad-leaved forest	Coniferous forest
1	Annual Precipitation	Bio12	62.3	16.9
2	Elevation	Elev	26.5	55.1
3	Precipitation Seasonality (Coefficient of Variation)	Bio15	2.6	2.1
4	Mean Diurnal Range (Mean of monthly (max temp - min temp))	Bio2	2.5	9.2
5	Slope	Slp	1.9	5.4
6	Precipitation of Coldest Quarter	Bio19	1.8	4.9
7	Aspect	Asp	1.2	2.8
8	Isothermality (BIO2/BIO7) ($\times$ 100)	Bio3	0.8	1
9	Mean Temperature of Driest Quarter	Bio9	0.3	1.9
10	Precipitation of Driest Month	Bio14	0.2	0.7

References

Adhikari, P., Shin, M.S., Jeon, J.Y., Kim, H.W., Hong, S., Seo, C., 2018. Potential impact of climate change on the species richness of subalpine plant species in the mountain national parks of South Korea. J. Ecol. Environ. 42 (1), 1–10. https://doi.org/10.1186/s41610-018-0095-y.

Allouche, O., Tsoar, A., Kadmon, R., 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). J. Appl. Ecol. 43 (6), 1223–1232. https://doi.org/10.1111/j.1365-2664.2006.01214.x.

Aryal, A., Brunton, D., Raubenheimer, D., 2014. Impact of climate change on human-wildlife-ecosystem interactions in the Trans-Himalaya region of Nepal. Theor. Appl. Climatol. 115 (3–4), 517–529. https://doi.org/10.1007/s00704-013-0902-4.

Bai, F., Sang, W., Axmacher, J.C., 2011. Forest vegetation responses to climate and environmental change: a case study from Changbai Mountain, NE China. For. Ecol. Manage. 262 (11), 2052–2060. https://doi.org/10.1016/j.foreco.2011.08.046.

Baral, K., Adhikari, B., Bhandari, S., Kunwar, R.M., Sharma, H.P., Aryal, A., Ji, W., 2023. Impact of climate change on distribution of common leopard (Panthera pardus) and its implication on conservation and conflict in Nepal. Heliyon 9 (1), e12807. https://doi.org/10.1016/j.heliyon.2023.e12807.

Barbet-Massin, M., Jiguet, F., Albert, C.H., Thuiller, W., 2012. Selecting pseudo-absences for species distribution models: how, where and how many? Methods Ecol. Evol. 3 (2), 327–338. https://doi.org/10.1111/j.2041-210X.2011.00172.x.

Bhatta, K.P., Aryal, A., Baral, H., Khanal, S., Acharya, A.K., Phomphakdy, C., Dorji, R., 2021. Forest structure and composition under contrasting precipitation regimes in the high mountains, western Nepal. Sustainability (Switzerland) 13 (13). https://doi.org/10.3390/su13137510.

Bhattacharjee, A., Anadón, J.D., Lohman, D.J., Doleck, T., Lakhankar, T., Shrestha, B.B., Thapa, P., Devkota, D., Tiwari, S., Jha, A., Siwakoti, M., Devkota, N.R., Jha, P.K., Krakauer, N.Y., 2017. The impact of climate change on biodiversity in Nepal: current knowledge, lacunae, and opportunities. Climate 5 (4). https://doi.org/10.3390/cli5040080.

Chhetri, P.K., Gaddis, K.D., Cairns, D.M., 2018. Predicting the suitable habitat of treeline species in the nepalese himalayas under climate change. Mt Res. Dev. 38 (2), 153–163. https://doi.org/10.1659/MRD-JOURNAL-D-17-00071.1.

Chiti, T., Díaz-Pinés, E., Rubio, A., 2012. Soil organic carbon stocks of conifers, broadleaf and evergreen broadleaf forests of Spain. Biol. Fertil. Soils 48 (7), 817–826. https://doi.org/10.1007/s00374-012-0676-3.

DFRS, 2015a. *High Mountains and High Himal Forests of Nepal* (Issue 4). Department of Forest Research and Survey, Kathmandu, Nepal.

DFRS, 2015b. *Middle Mountains Forests of Nepal: Forest Resource Assessment (FRA)* (Issue 3). Department of Forest Research and Survey, Kathmandu, Nepal.

EGGERS, J., LINDNER, M., ZUDIN, S., ZAEHLE, S., LISKI, J., 2008. Impact of changing wood demand, climate and land use on European forest resources and carbon stocks during the 21st century. Glob. Chang. Biol. 14 (10), 2288–2303. https://doi.org/10.1111/j.1365-2486.2008.01653.x.

Elith, J., Graham, C.H., Anderson, R.P., Dudík, M., Ferrier, S., Guisan, A., Hijmans, R.J., Huettmann, F., Leathwick, J.R., Lehmann, A., Li, J., Lohmann, L.G., Loiselle, B.A., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton, J.M.McC., Townsend Peterson, A., Zimmermann, N.E., 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography 29 (2), 129–151. https://doi.org/10.1111/j.2006.0906-7590.04596.x.

ESRI, 2017. ArcGIS Desktop: release 10.5. Environmental Systems Research. Redlands, California, USA.

Feeley, K.J., Davies, S.J., Perez, R., Hubbell, S.P., Foster, R.B., 2011. Directional changes in the species composition of a tropical forest. Ecology 92 (4), 1–12. https://doi.org/10.1890/10-0724.1.

Fortin, M.J., 1999. Effects of sampling unit resolution on the estimation of spatial autocorrelation. Ecoscience 6, 636–641.

Fyllas, N.M., Koufaki, T., Sazeides, C.I., Spyroglou, G., Theodorou, K., 2022. Potential impacts of climate change on the habitat suitability of the dominant tree species in Greece. Plants 11 (12), 1616. https://doi.org/10.3390/plants11121616.

Gajurel, J.P., Werth, S., Shrestha, K.K., Scheidegger, C., 2014. Species distribution modeling of Taxus wallichiana (Himalayan Yew) in Nepal Himalaya. Asian J. Conserv. Biol. 3 (2), 43.

Gauli, A., Neupane, P.R., Mundhenk, P., Köhl, M., 2022. Effect of climate change on the growth of tree species: dendroclimatological analysis. Forests 13 (4), 1–16. https://doi.org/10.3390/f13040496.

Gebeyehu, M.N., 2019. Review on effect of climate change on forest ecosystem. Int. J. Environ. Sci. Nat. Resour. 17 (4) https://doi.org/10.19080/ijesnr.2019.17.555968.

GoN/MoFE, 2021. Third National Communication to the United Nations. Ministry of Forest and Soil Conservation (MFSC), Kathmandu, Nepal.

Grimmett, L., Whitsed, R., Horta, A., 2020. Presence-only species distribution models are sensitive to sample prevalence: evaluating models using spatial prediction stability and accuracy metrics. Ecol. Modell. 431, 109194 https://doi.org/10.1016/j.ecolmodel.2020.109194.

Hanawalt, R.B., Wittaker, R.H., 1976. Altitudinally coordinated patterns of soils and vegetation in the San Jacinto mountains, California. Soil Sci. 121 (2), 114–124. https://doi.org/10.1097/00010694-197602000-00007.

Heidenreich, M.G., Seidel, D., 2022. Assessing Forest vitality and forest structure using 3D data: a case study from the Hainich National Park, Germany. Front. Forests Glob. Change 5 (June), 1–12. https://doi.org/10.3389/ffgc.2022.929106.

Hiura, T., Go, S., Iijima, H., 2019. Long-term forest dynamics in response to climate change in northern mixed forests in Japan: a 38-year individual-based approach. For. Ecol. Manage. 449, 117469 https://doi.org/10.1016/j.foreco.2019.117469.

Hufnagel, L., Garamvölgyi, Á., 2014. Impacts of climate change on vegetation distribution. Appl. Ecol. Environ. Res. 12 (2), 355–422. https://doi.org/10.15666/aeer/1202_355422.

IPCC, 2013. Annex III: glossary [Planton, S. (ed.)]. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel On Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC, 2018. Global Warming of 1.5°C. An IPCC Special Report On the Impacts of Global Warming of 1.5°C Above Pre-Industrial Levels and Related Global Greenhouse Gas Emission pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change. Cambridge University Press, Cambridge, UK and New York, NY, USA. https://doi.org/10.1017/9781009157940 (A. P. [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, and T. W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, & W. (eds.)] (eds.)).

IPCC. (2023). *AR6 Sythesis report: climate change 2023*.

Joshi, V.C., Bisht, D., Sundriyal, R.C., Pant, H., 2022. Species richness, diversity, structure, and distribution patterns across dominating forest communities of low and mid-hills in the Central Himalaya. Geol. Ecol. Landsc.s 00 (00), 1–11. https://doi.org/10.1080/24749508.2021.2022424.

Keane, R.E., Holsinger, L.M., Loehman, R., 2020. Bioclimatic modeling of potential vegetation types as an alternative to species distribution models for projecting plant species shifts under changing climates. For. Ecol. Manage. 477, 118498 https://doi.org/10.1016/j.foreco.2020.118498.

Kelly, A.E., Goulden, M., 2008a. Rapid shifts in plant distribution with recent climate change. Proc. Natl. Acad. Sci. U.S.A. 105 (33), 11823–11826. https://doi.org/10.1073/pnas.0802891105.

Kelly, A.E., Goulden, M.L., 2008b. Rapid shifts in plant distribution with recent climate change. Proc. Natl. Acad. Sci. U.S.A. 105 (33), 11823–11826. https://doi.org/10.1073/pnas.0802891105.

Lamsal, P., Kumar, L., Atreya, K., Pant, K.P., 2017. Vulnerability and impacts of climate change on forest and freshwater wetland ecosystems in Nepal: a review. Ambio 46 (8), 915–930. https://doi.org/10.1007/s13280-017-0923-9.

Lenoir, J., Gégout, J.C., Dupouey, J.L., Bert, D., Svenning, J.-C., 2010. Forest plant community changes during 1989-2007 in response to climate warming in the Jura Mountains (France and Switzerland). J. Vegetat. Sci. 21 (5), 946–964. https://doi.org/10.1111/j.1654-1103.2010.01201.x.

Li, Y., Li, M., Li, C., Liu, Z., 2020. Optimized maxent model predictions of climate change impacts on the suitable distribution of cunninghamia lanceolata in China. Forests 11 (3). https://doi.org/10.3390/f11030302.

Lindner, M., Maroschek, M., Netherer, S., Kremer, A., Barbati, A., Garcia-Gonzalo, J., Seidl, R., Delzon, S., Corona, P., Kolström, M., Lexer, M.J., Marchetti, M., 2010. Climate change impacts, adaptive capacity, and vulnerability of European forest ecosystems. For. Ecol. Manage. 259 (4), 698–709. https://doi.org/10.1016/j.foreco.2009.09.023.

Lobo, J.M., Jiménez-valverde, A., Real, R., 2008. AUC: a misleading measure of the performance of predictive distribution models. Glob. Ecol. Biogeogr. 17 (2), 145–151. https://doi.org/10.1111/j.1466-8238.2007.00358.x.

Mahatara, D., Acharya, A.K., Dhakal, B.P., Sharma, D.K., Ulak, S., Paudel, P., 2021. Maxent modelling for habitat suitability of vulnerable tree Dalbergia latifolia in Nepal. Silva Fennica 55 (4), 1–17. https://doi.org/10.14214/sf.10441.

Malla, R., Neupane, P.R., Köhl, M., 2022. Modelling soil organic carbon as a function of topography and stand variables. Forests 1–14. https://doi.org/10.3390/f13091391.

Manish, K., Telwala, Y., Nautiyal, D.C., Pandit, M.K., 2016. Modelling the impacts of future climate change on plant communities in the Himalaya: a case study from Eastern Himalaya, India. Model. Earth Syst. Environ. 2 (2), 1–12. https://doi.org/10.1007/s40808-016-0163-1.

Merow, C., Smith, M.J., Silander, J.A., 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. Ecography 36 (10), 1058–1069. https://doi.org/10.1111/j.1600-0587.2013.07872.x.

Mishra, B., Panthi, S., Poudel, S., Ghimire, B.R., 2023. Forest fire pattern and vulnerability mapping using deep learning in Nepal. Fire Ecol. 19 (1) https://doi.org/10.1186/s42408-022-00162-3.

Naimi, B., Hamn, N.a.s., Thomas, A., Andrew, G., K, S., Toxopeus, A.G, 2023. Where is positional uncertainty a problem for species distribution modeling. Ecography 37, 191–203.

Nogués-Bravo, D., Araújo, M.B., Errea, M.P., Martínez-Rica, J.P., 2007. Exposure of global mountain systems to climate warming during the 21st Century. Glob. Environ. Change 17 (3), 420–428. https://doi.org/10.1016/j.gloenvcha.2006.11.007.

Parmesan, C., & Yohe, G. (2003). *Aglobally coherent fingerprint of climate change impacts across natural systems*. 37–42. 10.1038/nature01286.

Paudel, G., Adhikari, S., Jojiju, B., Adhikari, R., Adhikar, N.P., 2021. Impact of climate change on the ecosystem of the central Himalayas, Nepal. Arch. Agric. Environ. Sci. 6 (3), 360–366. https://doi.org/10.26832/24566632.2021.0603015.

Pearce, J., Ferrier, S., 2000. Evaluating the predictive performance of habitat models developed using logistic regression. Ecol. Modell. 133 (3), 225–245. https://doi.org/10.1016/S0304-3800(00)00322-7.

Pepin, N.C., Seidel, D.J., 2005. A global comparison of surface and free-air temperatures at high elevations. J. Geophys. Res. D Atmos. 110 (3), 1–15. https://doi.org/10.1029/2004JD005047.

Phillips, S.B., Aneja, V.P., Kang, D., Arya, S.P., 2006. Modelling and analysis of the atmospheric nitrogen deposition in North Carolina. Int. J. Glob. Environ. Issues 6 (2–3), 231–252. https://doi.org/10.1016/j.ecolmodel.2005.03.026.

Pureswaran, D.S., Roques, A., Battisti, A., 2018. Forest insects and climate change. Curr. Forestry Rep. 4 (2), 35–50. https://doi.org/10.1007/s40725-018-0075-6.

Rai, R., Zhang, Y., Liu, L., Singh, P.B., Paudel, B., Acharya, B.K., Khanal, N.R., 2022a. Predicting the impact of climate change on vulnerable species in Gandaki River Basin, Central Himalayas. J. Resour. Ecol. 13 (2), 173–185. https://doi.org/10.5814/j.issn.1674-764x.2022.02.001.

Rai, R., Zhang, Y., Wang, Z., Paudel, B., Liu, L., Rai, M.K., Khanal, N.R., 2022b. Use of the MaxEnt model to predict changes in sloth bear (Melursus ursinus) habitats in the Gandaki River Basin, Nepal. J. Mt. Sci. 19 (7), 1988–1997. https://doi.org/10.1007/s11629-021-7271-8.

Rana, S.K., Rana, H.K., Ranjitkar, S., Ghimire, S.K., Gurmachhan, C.M., O'Neill, A.R., Sun, H, 2020. Climate-change threats to distribution, habitats, sustainability and conservation of highly traded medicinal and aromatic plants in Nepal. Ecol. Indic. 115, 106435 https://doi.org/10.1016/j.ecolind.2020.106435.

Rigling, A., Bigler, C., Eilmann, B., Feldmeyer-Christe, E., Gimmi, U., Ginzler, C., Graf, U., Mayer, P., Vacchiano, G., Weber, P., Wohlgemuth, T., Zweifel, R., Dobbertin, M., 2013. Driving factors of a vegetation shift from Scots pine to pubescent oak in dry Alpine forests. Glob. Chang. Biol. 19 (1), 229–240. https://doi.org/10.1111/gcb.12038.

Shrestha, U.B., Lamsal, P., Ghimire, S.K., Shrestha, B.B., Dhakal, S., Shrestha, S., Atreya, K., 2022. Climate change- - induced distributional change of medicinal and aromatic plants in the Nepal Himalaya. July 1–14. https://doi.org/10.1002/ece3.9204.

Shrestha, U.B., Sharma, K.P., Devkota, A., Siwakoti, M., Shrestha, B.B., 2018. Potential impact of climate change on the distribution of six invasive alien plants in Nepal. Ecol. Indic. 95 (July), 99–107. https://doi.org/10.1016/j.ecolind.2018.07.009.

Shrestha, U.B., Shrestha, B.B., 2019. Climate change amplifies plant invasion hotspots in Nepal. Divers. Distrib. 25 (10), 1599–1612. https://doi.org/10.1111/ddi.12963.

Singh, R., Kayastha, S.P., Pandey, V.P., 2022. Climate change and river health of the Marshyangdi Watershed, Nepal: an assessment using integrated approach. Environ. Res. 215, 114104 https://doi.org/10.1016/j.envres.2022.114104.

Siwakoti, M., Shrestha, B.B., Devkota, A., Shrestha, U.B., Thapaparajuli, R.B., Sharma, K. P., et al., 2016. Assessment of the effects of climate change on distribution of invasive alien species in Nepal. In: Bhuju, D., McLaughlin, K., Sijapati, J., Devkota, B., Shrestha, N., Ghimire, G.P., et al. (Eds.), Building Knowledge for Climate Resilience in Nepal: Research Brief. Nepal Academy of Science and Technology Khumaltar, Lalitpur. October.

Stainton, J.D.A., 1972. Forests of Nepal. *Taxon* (Vol. 22, Issue 1). John Murray, London. https://doi.org/10.2307/1218063.

Su, H., Bista, M., Li, M., 2021. Mapping habitat suitability for Asiatic black bear and red panda in Makalu Barun National Park of Nepal from Maxent and GARP models. Sci. Rep. 11 (1), 1–14. https://doi.org/10.1038/s41598-021-93540-x.

Taccoen, A., Piedallu, C., Seynave, I., Gégout-Petit, A., Gégout, J.C., 2022. Climate change-induced background tree mortality is exacerbated towards the warm limits of the species ranges. Ann. For. Sci. 79 (1), 1–22. https://doi.org/10.1186/s13595-022-01142-y.

Thapa, G.J., Wikramanayake, E., Forrest, J., 2013. *Climate-change impacts on the biodiversity of the Terai Arc landscape and the Chitwan-Annapurna landscape*. Hariyo Ban, WWF, Nepal, Kathmandu, Nepal.

Thapa, U.K., St. George, S., 2019. Detecting the influence of climate and humans on pine forests across the dry valleys of eastern Nepal's Koshi River basin. For. Ecol. Manage. 440 (March), 12–22. https://doi.org/10.1016/j.foreco.2019.03.013.

Thuiller, W., Lavorel, S., Sykes, M.T., Araújo, M.B., 2006. Using niche-based modelling to assess the impact of climate change on tree functional diversity in Europe. Divers. Distrib. 12 (1), 49–60. https://doi.org/10.1111/j.1366-9516.2006.00216.x.

Tian, L., Fu, W., 2020. Bi-temporal analysis of spatial changes of boreal forest cover and species in Siberia for the years 1985 and 2015. Remote Sens. (Basel) 12 (24), 1–14. https://doi.org/10.3390/rs12244116.

Toledo, M., Poorter, L., Peña-Claros, M., Alarcón, A., Balcázar, J., Leaño, C., Licona, J.C., Llanque, O., Vroomans, V., Zuidema, P., Bongers, F., 2011. Climate is a stronger driver of tree and forest growth rates than soil and disturbance. J. Ecol. 99 (1), 254–264. https://doi.org/10.1111/j.1365-2745.2010.01741.x.

Trisurat, Y., Alkemade, R., Arets, E., 2009. Projecting forest tree distributions and adaptation to climate change in northern Thailand. J. Ecol. Nat. Environ. 1 (3), 55–63.

Wang, W.J., Thompson, F.R., He, H.S., Fraser, J.S., Dijak, W.D., Jones-Farrand, T., 2019. Climate change and tree harvest interact to affect future tree species distribution changes. J. Ecol. 107 (4), 1901–1917. https://doi.org/10.1111/1365-2745.13144.

Wiley, E.O., McNyset, K.M., Peterson, A.T., Robins, C.R., Stewart, A.M., 2003. Niche modeling and geographic range predictions in the marine environment using a machine-learning algorithm. Oceanography 16 (SPL.ISS. 3), 120–127. https://doi.org/10.5670/oceanog.2003.42.

Wu, Z.Z.Z., Dai, E., Wu, Z.Z.Z., Lin, M., 2019. Future forest dynamics under climate change, land use change, and harvest in subtropical forests in Southern China. Landsc. Ecol. 34 (May), 843–863. https://doi.org/10.1007/s10980-019-00809-8.

Xiao-Ying, W., Chun-Yu, Z., Qing-Yu, J., 2013. Impacts of climate change on forest ecosystems in Northeast China. Adv. Clim. Change Res. 4 (4), 230–241. https://doi.org/10.3724/SP.J.1248.2013.230.

Xie, D., Du, H., Xu, W.H., Ran, J.H., Wang, X.Q., 2022. Effects of climate change on richness distribution patterns of threatened conifers endemic to China. Ecol. Indic. 136, 108594 https://doi.org/10.1016/j.ecolind.2022.108594.

Xu, J., Grumbine, R.E., Shrestha, A., Eriksson, M., Yang, X., Wang, Y., Wilkes, A., 2009. The melting Himalayas: cascading effects of climate change on water, biodiversity, and livelihoods. Conserv. Biol. 23 (3), 520–530. https://doi.org/10.1111/j.1523-1739.2009.01237.x.

Zhao, Y., Liu, Y.L., Guo, Z.T., Fang, K.Y., Li, Q., Cao, X.Y., 2017. Abrupt vegetation shifts caused by gradual climate changes in central Asia during the Holocene. Sci. China Earth Sci. 60 (7), 1317–1327. https://doi.org/10.1007/s11430-017-9047-7.

Zhou, G., Peng, C., Li, Y., Liu, S., Zhang, Q., Tang, X., Liu, J., Yan, J., Zhang, D., Chu, G., 2013. A climate change-induced threat to the ecological resilience of a subtropical monsoon evergreen broad-leaved forest in Southern China. Glob. Chang. Biol. 19 (4), 1197–1210. https://doi.org/10.1111/gcb.12128.