



How will forest fires impact the distribution of endemic plants in the Himalayan biodiversity hotspot?

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Abstract

Global warming is causing shifts in distribution of plants, leading to alterations in the native flora. In addition, increased intensity and frequency of wildfires is posing threats to Himalayan ecosystems. Modeling a species' ecological niche and its potential distribution under projected impacts of climate change and distribution of wildfires provides an understanding of the behavior of native flora in altered climatic conditions. In this study, we predicted future distribution of four endemic tree species *Pinus roxburghii*, *Quercus semecarpifolia*, *Rhododendron arboretum*, and *Cedrus deodara* in western Himalaya under A1B scenario of Special Report on Emission Scenarios for 2030, 2050, and 2080, under two conditions: (i) without wildfire and (ii) with wildfire. We included wildfire occurrence as a predictor variable in the *Maxent* model along with 35 climate variables, to predict the future distribution of four indicator species. As per the predictions, there will be a significant reduction in the geographic distribution of the indicator species under the 'with wildfire' scenario as compared to the 'without wildfire' scenario. The future distribution range was shifted towards the northern and north-eastern regions of our study area owing to higher moisture availability. We predicted reduction in the range of *C. deodara* during 2030, *R. arboretum* during 2050, and *P. roxburghii* during 2080, while the distribution of *Q. semecarpifolia* remained unchanged. Our modeling predicted that climate change could induce reduction, expansion, and shift in the distributions of endemic plant species, which could lead to alteration in the endemic flora of the Himalayas.

Keywords Species distribution modelling · Wildfire · Climate change scenario · Maximum entropy method

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Introduction

Impacts of climate change on terrestrial ecosystems

During last three decades global mean temperature has increased by 0.85 °C relative to the mean temperature during 1986–2005 (IPCC 2013). According to Representative concentration pathway (RCP) 2.6 it is likely to increase further by a minimum of 0.3 °C–1.7 °C, and, as forecast by RCP 8.5 by up to a maximum of 2.6 °C–4.8 °C by the end of this century (IPCC 2013). The forecasted increase in global mean temperature is neither temporally nor spatially uniform (Bellard et al. 2012). Climate change is expected to cause shifts in species' ranges globally as species track their optimal niche, which will likely shift as a result of rearrangement of climate zones (Loarie et al. 2008a, b; Velásquez-Tibatá et al. 2012). High elevation and high latitude areas are among those regions where rates of warming are forecast to be higher than the global average rates. Temperature-limited environments such as high mountains are thought to be very sensitive to climate change. Global climate change over last few decades has caused numerous shifts in the distribution and abundance of mountain ecosystems (Araujo et al. 2011, Chen et al. 2011). The rate of regional warming in parts of the Himalayas has exceeded the rate of global warming (Chaudhari and Bawa 2011). Climate change induced vegetation shift towards higher elevations and higher latitudes poses threats to the mountain ecosystems by intensifying the competition for survival, leading to species extinction (Ashcroft 2010). Globally, climate change over last few decades has caused shifts in the distribution of plant species at varying degrees (Kueppers et al. 2005; Kelly and Goulden 2008; Loarie et al. 2008a, b; Chen et al. 2011). In addition, Himalayan ecosystems are experiencing a higher degree of species extinction as well as alterations in species distribution due to altered climatic extremes, rising temperatures, erratic rainfall pattern (Chitale et al. 2014; Thapa et al. 2018). Projecting the changes in the distribution of endemic plants under future climatic conditions might provide important information for planning and mitigating the impacts of climate change on native ecosystems (Araujo and Rahbek 2006).

Impact of wildfires on forests

Wildfires occur in three principal forms as Surface fires, Crown fires, and Ground fires depending on their means of spread and their position to the ground (Semwal and Mehta 1996; Roy 2004). Vegetation type and density are the two most important floristic factors related to ignition of wildfires. Surface fires are common and have been documented in wildfire-prone forests in the western Himalaya (Roy 2004). In India about 3.73 million ha of forests are annually affected by wildfires (Chandra and Bhardwaj 2015). The effect of wildfires on vegetation dynamics mainly includes the changes in composition and structure of the communities (Kittur et al. 2014). Fires affect the floristic composition of ecosystems by selectively favoring fire-adapted species and destroying the non-fire resistant species (De Bano et al. 1998). The timing and periodicity of fires is of extreme importance in some plant communities as these factors affect plant survival and flowering, whereas fire intensity affects the resistance of woody plants and seed germination (Trabaud 1987; Wheelan 1995; Verma and Jayakumar 2015). Fires also have an indirect effect of introducing invasive species and affecting the native biodiversity. Wildfires affect soil properties through changing soil microbial activities and water relations, and creating heterogeneous mosaics,

which in turn, can further influence fire behavior and ecological processes (Certini 2005). As an evolutionary mechanism, some plants have thick bark, capability of re-sprouting, and meristem and seed protection strategies to cope up with the recurring wildfires (Bond and van Wilgen 1996). A study by Slik et al. (2002) showed that wildfire changes the forest structure by significantly reducing the numbers of trees and species in the forest area. Considering the positive and negative roles of wildfires in mediating and regulating ecosystems, they should be incorporated as an integral component of ecosystems and management. Nonetheless, there have been no studies on understanding and predicting the role of wildfires on future distribution of plants.

Climatic, topographic, and geological variations have resulted in unique ecosystems and biota in the Himalayas (Myers et al. 2000; Singh 2019). High calorific value, aggressive middle storey vegetation, and the slow-growing nature of the Himalayan forests make them vulnerable to this new threat fuelled by a warming climate (Sharma et al. 2010; Ahmad and Goparaju 2018). Warming summers and less annual rainfall in recent decades due to climate change have increased the frequency of occurrence and severity of wildfires across the globe (North et al. 2015; Murthy et al. 2019). Wildfire is considered part of the normal 'climate' in most of the terrestrial ecosystems (Semwal and Mehta 1996). But the increased frequency of wildfire events results in warming and thus alters the biodiversity of the Indian Himalayan biodiversity hotspot. *Pinus roxburghii* produces resins and hence accommodates the highest frequencies of wildfire events compared to other endemic tree species. *Cedrus deodara*, *Quercus semecarpifolia*, and *Rhododendron arboreum* are often juxtaposed with *P. roxburghii* in habitats where there is higher probability of damage due to crown fires. The destruction of flora and fauna caused by wildfires during summer season in the western Himalayan forests is greater than by any other anthropogenic factor on these forests (Sahni 1990; Hussain et al. 2018). Hence, there is an urgent need to study the impact of the wildfires on the endemic flora of the Himalaya, considering that the mean temperature has risen by more than 1 °C during 1970–2002 (McDowell 2002) and continued increase is predicted over the coming two decades (Shrestha and Bawa 2014) that will increase the wildfire events.

Species distribution modelling

Impact of climate change is evident globally on increasing number of species (Fitter and Fitter 2002; Cotton 2003; Iverson et al. 2008). Various researchers have anticipated range shifts and extinctions of high elevation flora due to increasing temperatures over the coming five decades (Araujo and Rahbek 2006; Iverson et al. 2008; Loarie et al. 2008a, b). Estimates of the future effects of global climate change on biodiversity have often been based on environmental envelope models (Moradi et al. 2019). Species distribution modelling is one of the methods used to quantify patterns of species and to extrapolate distributions across space and time based on a statistical model. These models assume that distributions are caused by the environmental tolerances that define fundamental niches (Leach et al. 2013). These models often relate known species distributions to predictor environmental variables to predict future potential distributions under global change scenarios (Guisan and Thuiller 2005; Phillips et al. 2006; Hannah et al. 2007; Iverson et al. 2008). Most of the studies have used climate factors alone to project species distributions under future scenarios; however, there are many other non-climatic factors that can affect potential distribution of species (Hampe 2004; Melles et al. 2010). This is particularly true for

high mountain ecosystems, where wildfire could alter the future distribution of the native flora.

Various studies have included non-climatic factors for modeling present-day species distributions. Such factors include land use and land cover (Thuiller et al. 2004; Pearson et al. 2004; Luoto et al. 2006), vegetation cover (Matin et al. 2012), topography (Luoto and Heikkinen 2007; Chitale and Behera 2012), or a combination of all these (Brotons et al. 2007), and vegetation structure and landscape configuration (Trivino et al. 2011). Rising temperatures in the Himalayas are expected to increase the intensity and frequency of occurrence of wildfires, which could accelerate the rate of degradation of Himalayan biodiversity. Global change scenarios based on environmental variables used in the species distribution models do not account for factors such as wildfires that affect regional climate (Nakicenovic et al. 2000).

To our knowledge, past studies have not considered wildfire event as a predictor variable in predicting the species distribution, particularly in the Himalayan ecosystems. The question arises: how the changes in temperature due to wildfire events affect future distribution of species? In this study, we addressed this question using occurrence data of four dominant endemic tree species in the western Himalaya (Fig. 1), viz. *Pinus roxburghii*

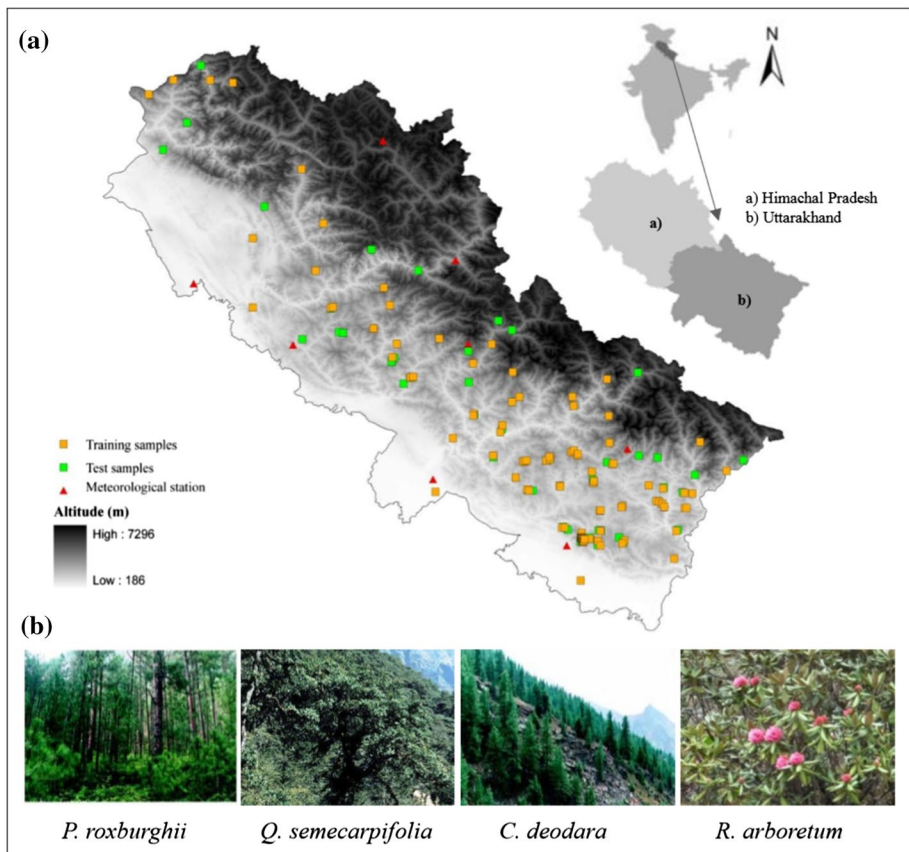


Fig. 1 **a** Location of training samples, test samples and meteorological stations overlaid on a digital elevation model of the study area; **b** photographs indicating ecological details of the indicator species

Table 1 Niche parameters of indicator plant species

Sl. no.	Species	Family	Altitude (m.a.s.l.)	Temperature (°C)	Precipitation (mm)
1	<i>Pinus roxburghii</i>	Pinaceae	450–2300	0–30	1000–1200
2	<i>Quercus semecarpifolia</i>	Fagaceae	2500–3800	0–30	500–2500
3	<i>Cedrus deodara</i>	Pinaceae	1200–3500	0–17	300–2000
4	<i>Rhododendron arboreum</i>	Ericaceae	1200–3800	0–20	200–1800

(Pine), *Quercus semecarpifolia* (Kharsu Oak), *Cedrus deodara* (Devdar) and *Rhododendron arboreum* (Burans) (see Table 1). Former three species are endemic to Himalayas and are known as key species of subtropical forests, while tree rhododendron is endemic to whole Asia and, in India, it is the state tree of Uttarakhand and the state flower of Himachal Pradesh. We studied the changes in predicted distribution of these four species under with- and without-wildfire condition for year 2030, 2050, and 2080 under SRES A1B scenario.

Methods

Study area

The study area covered Himachal Pradesh and Uttarakhand States of India, covering 109,156 km² of forests that experience the greatest annual numbers of forest fires (Kelkar et al. 2008). The study area encompassed 716, 84 km² of forest cover with diverse vegetation communities (Fig. 1). In summer 2016, a large portion of the forests in Uttarakhand burned during the infamous Uttarakhand forest fire incident. This resulted in damage to forest resources estimated at billions of rupees, caused the death of 6 people, and killed hundreds of wild animals (Gupta et al. 2018). We observed an increasing trend of wildfire occurrence from 2009 to 2012. In 2009, 797 wildfires occurred in the study area, which increased to 984 in 2010, to 1104 in 2011, and to 1498 by 2012.

Species distribution modelling

We used MaxEnt model (version 3.3.3e) that works on the maximum entropy method (Phillips et al. 2006), to conduct the species distribution modelling and assess the changes in distribution of indicator species under two scenarios, (i) with wildfires and (ii) without wildfires (Fig. 2). Maxent is a general-purpose machine learning method with a simple and precise mathematical formulation, and it has a number of aspects that make it well-suited for species distribution modeling. The model was formulated by Phillips et al. (2006) and first implemented over the Amazonian region.

The Maxent model uses *training* samples to simulate the scenario of prediction against a set of bioclimatic variables, which are mostly climatic and physiographic indicators of the niche, and the model uses *test* samples to assess the accuracy of modeling while attempting to estimate a probability distribution of species occurrence that is closest to uniform while still subject to environmental constraints (Elith et al. 2011). We used the free version of Maxent software, version 3.3.3e (<http://www.cs.princeton.edu/~schapire/maxent/>), which generates an estimate of probability of presence of the species that varies from 0 to 1, i.e.

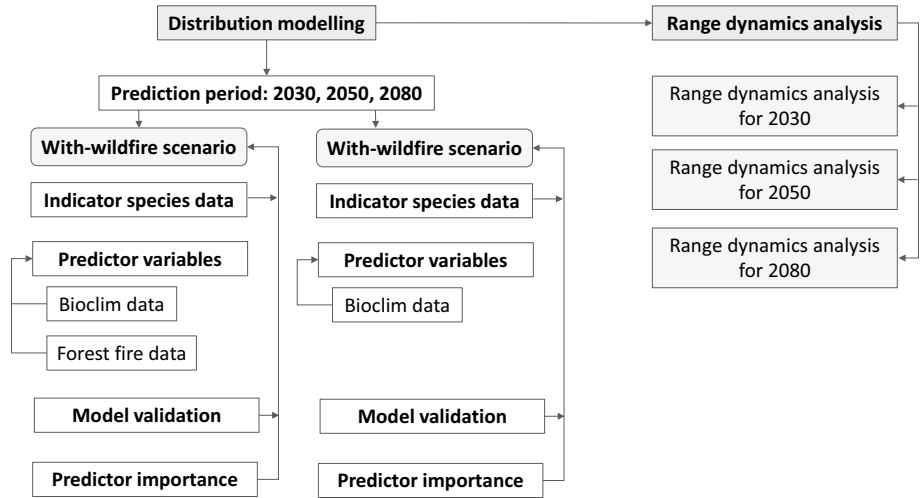


Fig. 2 Methodology flowchart

from the lowest to the highest probability. Maxent works best with the presence only datasets viz., locations of presence records of the species and produces precise results with few samples as well, hence it is a suitable modelling technique to be used for endemic species (Leach et al. 2013). Therefore, we used this modelling technique for our study.

Plant distribution data

Based on the plant distribution data of ‘*Biodiversity characterization project*’ (Roy et al. 2012), we selected four indicator species that are endemic to the study area and have highest species dominance compared to other endemic species. One hundred eighty-seven records were extracted from the field data of ‘*Biodiversity characterization project*’ (Roy et al. 2012) that contained geographical distribution of four indicator species. We used at least fifteen records of each species as *training* and *test* samples for running the model, as recommended by Leach et al. (2013). The occurrence records of the indicator species were split into *training* and *test* samples with a 70:30 proportion respectively using ‘random data splitting’ method. In total, we used 38 and 19 records of Pinus, 24 and 16 records of Quercus, 24 and 17 records of Cedrus, and 31 and 18 records of Rhododendron as training and test samples respectively. We assume this sample can be taken as representative of the part of the Himalayan flora distributed in India because it includes records of four dominant endemic tree species, which are currently exposed to the threat of increasing wildfire frequency. Throughout this study we refer to the baseline distributions of our four indicator species as their “2008 distributions” because 2008 was the final year of the national biodiversity survey project.

Predictor variables

Our predictor variables comprised of climate and disturbance factors (Table 2). We used the future climate prediction data for three time periods viz., 2030, 2050, and 2080

Table 2 Details of 35 bioclimatic variables acquired from CliMond database

Variable	Description
Bio01	Annual mean temperature (°C)
Bio02	Mean diurnal temperature range (mean(period max–min)) (°C)
Bio03	Isothermality (Bio02/Bio07)
Bio04	Temperature seasonality (C of V)
Bio05	Max temperature of warmest week (°C)
Bio06	Min temperature of coldest week (°C)
Bio07	Temperature annual range (Bio05–Bio06) (°C)
Bio08	Mean temperature of wettest quarter (°C)
Bio09	Mean temperature of driest quarter (°C)
Bio10	Mean temperature of warmest quarter (°C)
Bio11	Mean temperature of coldest quarter (°C)
Bio12	Annual precipitation (mm)
Bio13	Precipitation of wettest week (mm)
Bio14	Precipitation of driest week (mm)
Bio15	Precipitation seasonality (C of V)
Bio16	Precipitation of wettest quarter (mm)
Bio17	Precipitation of driest quarter (mm)
Bio18	Precipitation of warmest quarter (mm)
Bio19	Precipitation of coldest quarter (mm)
Bio20	Annual mean radiation ($W m^{-2}$)
Bio21	Highest weekly radiation ($W m^{-2}$)
Bio22	Lowest weekly radiation ($W m^{-2}$)
Bio23	Radiation seasonality (C of V)
Bio24	Radiation of wettest quarter ($W m^{-2}$)
Bio25	Radiation of driest quarter ($W m^{-2}$)
Bio26	Radiation of warmest quarter ($W m^{-2}$)
Bio27	Radiation of coldest quarter ($W m^{-2}$)
Bio28	Annual mean moisture index
Bio29	Highest weekly moisture index
Bio30	Lowest weekly moisture index
Bio31	Moisture index seasonality (C of V)
Bio32	Mean moisture index of wettest quarter
Bio33	Mean moisture index of driest quarter
Bio34	Mean moisture index of warmest quarter
Bio35	Mean moisture index of coldest quarter

under the IPCC A1B scenario, (Parry et al. 2007). The A1 scenario describes a world with rapid economic growth and population that peaks in mid-century and declines thereafter and assumes rapid introduction of new and more efficient technologies, while concentrations of carbon increase from 380 ppm in 2000 to 800 ppm in 2080, and temperature rises by 3.6 K. A1B is a subset of A1 family, which refers to a balanced emphasis on all energy sources (IPCC 2001). We used 35 bioclimatic variables with 10×10 kms spatial resolution from the CliMond database (<https://www.climond.org>, Table 1)

that represent biologically meaningful measures for characterizing species distributions. CliMond database provides crucial information on climate datasets of the study area and describe temperature, precipitation, solar radiation, and moisture index with annual mean, and lowest and highest extremes. For correlative species distribution models, the 10 × 10 kms climatology data from CliMond database provides an opportunity to the modeler to identify marginally climatically suitable locations and appears to support model projections that are ecologically meaningful (Kriticos et al. 2012). Hence, we used CliMond datasets of climate projections for year 2030, 2050, and 2080 under A1B scenario. A raster layer of fire disturbance was created based on the mean temperature of wildfire events and the spatial locations of wildfire events using Krigging spatial interpolation technique in ArcGIS. For this purpose, spatial locations of 4204 wildfire events that occurred in the States of Himachal Pradesh and Uttarakhand during year 2008 to 2012 were acquired from Forest Survey of India (<http://www.fsi.org.in/forest-fire.php>). The spatial layer of wildfire events was overlaid on the vegetation type map of the study area (Roy et al. 2012) in GIS environment ArcGIS 9.2 to generate separate raster layers of wildfire events that occurred in the areas containing Pinus, Quercus, Cedrus, and Rhododendron. Finally, the spatial resolution of all the predictor variables was set to 10' to match with the climate datasets. All the layers were converted to.csv (comma-separate values) match the format for the modelling in Maxent. We used the area under curve (AUC) values that range from 0 to 1 and provide the accuracy value of the prediction with training and test samples. The results with only above 90% estimation accuracy on training and testing samples were retained and used in the analysis.

Range dynamics

We analyzed the predicted distribution of all four indicator species under with-wildfire and without-wildfire conditions under 2030, 2050, and 2080 and quantified the range expansion and range reduction. We also analyzed the range expansion and range reduction across different classes of distribution probability e.g., 0–20%-very low; 20–30%-low; 30–40%-moderate; 40–60%-high; > 60%-very high probability.

Results

Prediction accuracy

The prediction accuracy of the model for the four indicator species under with-wildfire and without-wildfire was found to be > 90%, which is acceptable for using the prediction results for the further analysis. In case of Pinus, the AUC values for training data ranged from 0.92 to 0.978 for different time periods, whereas that for testing data ranged from 0.915 to 0.966 (Table 3). The AUC values for training data for Quercus ranged from 0.91 to 0.965, whereas that for the testing data ranged from 0.914 to 0.978. The AUC values for training and testing data Cedrus ranged from 0.911 to 0.96 and from 0.935 to 0.963 respectively. For Rhododendron, the AUC values for training and testing data ranged from 0.916 to 0.98 and from 0.915 to 0.948 respectively.

Table 3 Area under curve values for the different prediction categories

Prediction category	Type	AUC values for <i>Pinus roxburghii</i>	AUC values for <i>Quercus semecarpifolia</i>	AUC values for <i>Cedrus deodara</i>	AUC values for <i>Rhododendron arboreum</i>
2030 WOF	Training	0.92	0.965	0.925	0.98
2030 WOF	Testing	0.915	0.978	0.935	0.945
2030 WF	Training	0.94	0.935	0.92	0.922
2030 WF	Testing	0.93	0.914	0.945	0.948
2050 WOF	Training	0.978	0.955	0.915	0.916
2050 WOF	Testing	0.956	0.96	0.948	0.92
2050 WF	Training	0.932	0.91	0.911	0.935
2050 WF	Testing	0.963	0.936	0.938	0.94
2080 WOF	Training	0.948	0.925	0.96	0.945
2080 WOF	Testing	0.966	0.944	0.948	0.915
2080 WF	Training	0.935	0.95	0.925	0.927
2080 WF	Testing	0.923	0.93	0.963	0.933

Species wise niche dynamics

The four indicator plant species depicted different patterns in predicted distribution under future climate change scenarios under with-wildfire and without-wildfire scenarios. The models predicted a reduction in the future distribution of all four species particularly in high altitude areas (5500–7200 m) under with-wildfire condition in 2030, 2050, and 2080 (Fig. 3). However, the overall predicted changes suggest that distribution of the indicator species will shift in eastern and north-eastern direction. In case of *P. roxburghii* the range reduction was not so prominent in 2030 and 2050, however in 2080 a prominent range reduction was predicted in high altitude areas, along with range expansion in low altitude areas. This indicates that niche of this species will be altered more in the long time period (e.g., 2080) than in short/mid-term time period (e.g., 2030, 50). This is in line with the results from a similar study by Chakraborty and Joshi (2016). On the contrary, the niche of *Q. semecarpifolia* is predicted to change by 2030 (Fig. 4), with increased distribution range in high altitude areas, which indicates availability of more area for expansion of the species. This is in line with the results of Saran et al. (2010). We did not observe any significant changes in the predicted distribution of *Q. semecarpifolia* in mid-term and long-term time periods (e.g., 2050, 80). The predicted distribution of *C. deodara* depicted range expansion in high altitude, while reduction at low and moderate altitude in 2030 and 2080. In 2050, the niche of the species is predicted to expand in most of the study area. This shows varied response to short-term, mid-term, and long-term climate change. We predicted severe range reduction in the distribution of *R. arboreum* in 2050 and in 2080, while minor change in the distribution were predicted in 2030 (Fig. 4). This indicates that species' niche will get impacted in the mid-term period and might continue with the similar trend towards the long-term period.

We also analyzed the range reduction and expansion under different classes of predicted probability of distribution of the indicator plants, where the expansion-reduction varied according to indicator species (Fig. 5). In 2030, the predicted distribution of *Cedrus* showed maximum range expansion by ca. 30% in moderate probability class of

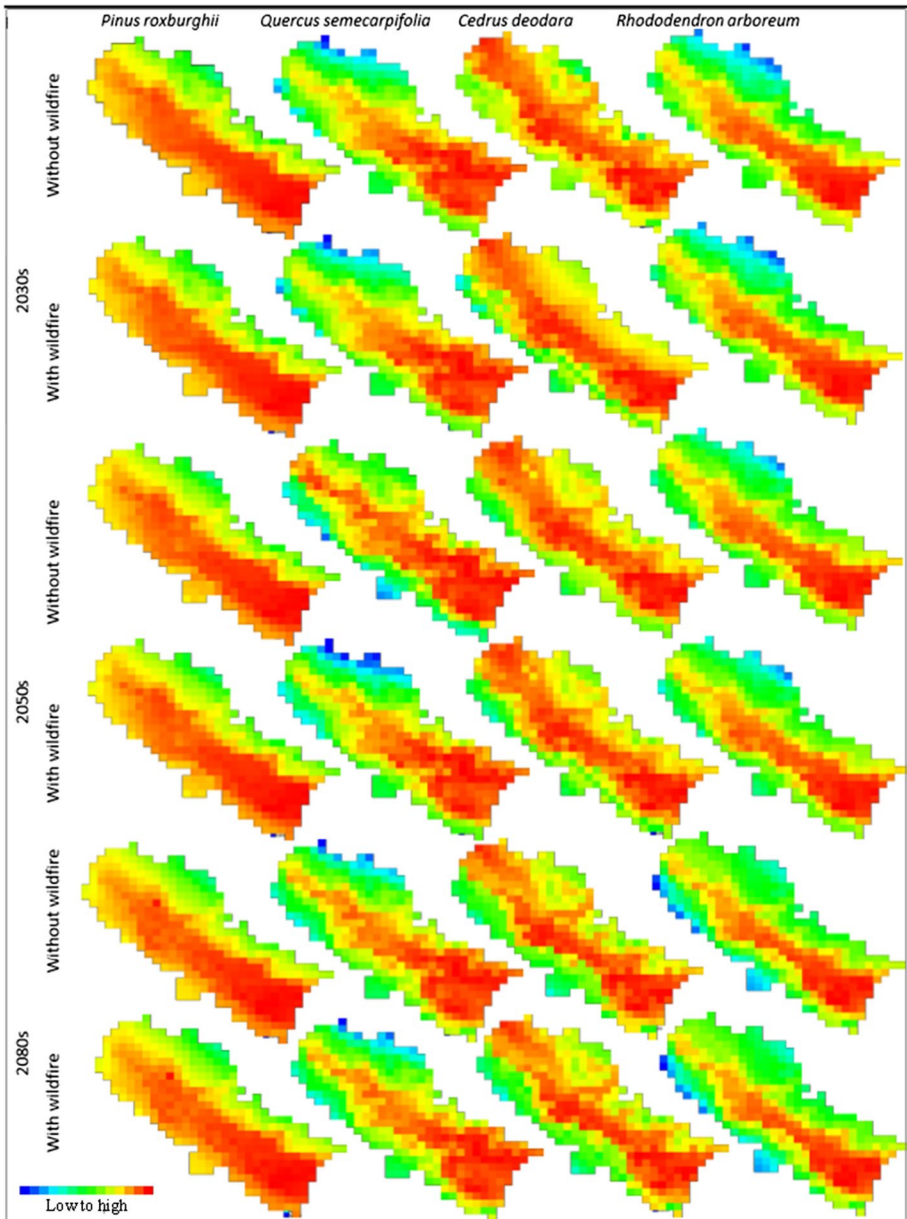


Fig. 3 Distribution of indicator species in 2030, 2050 and 2080 under without-wildfire and with-wildfire scenarios

distribution and range reduction in all other probability classes. *Quercus* also showed minor increase during 2030. In 2050, *Rhododendron* showed maximum range expansion in high probability distribution class, while range reduction was observed in all other

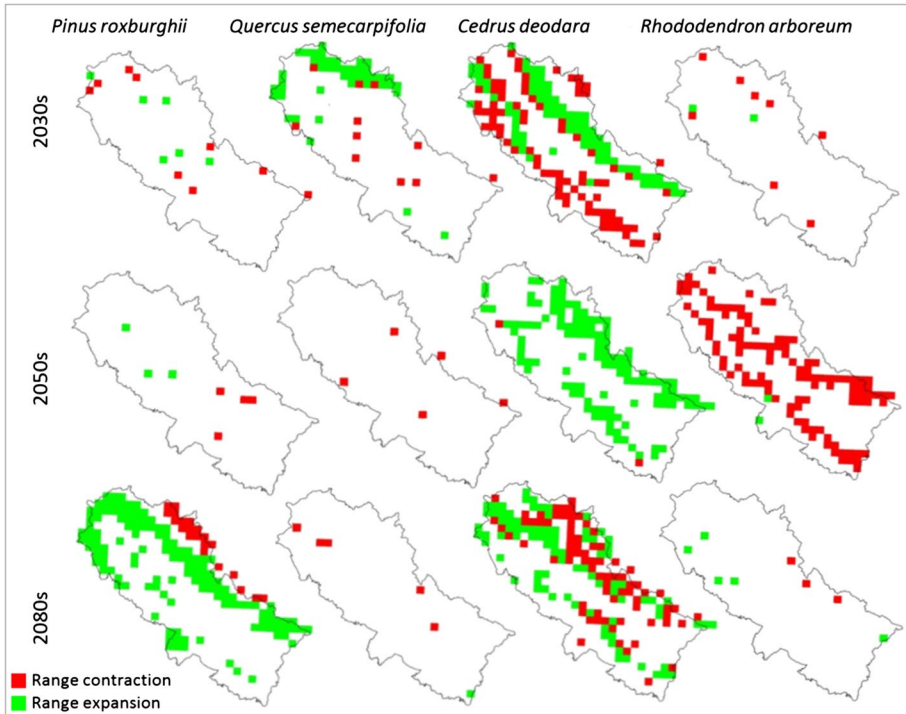


Fig. 4 Range reduction and expansion in the distribution of indicator species in year 2030, 2050 and 2080 caused by climatic variations in with- and without-wildfire scenarios

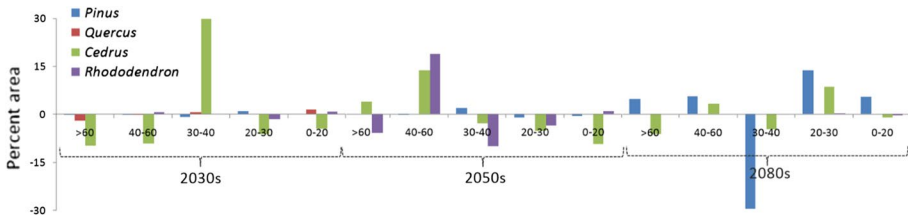


Fig. 5 Percent area under range expansion vs. reduction in the distribution of indicator species in year 2030, 2050 and 2080

probability classes, whereas in 2080, large range reduction was predicted in moderate probability distribution class of Pinus.

Role of predictor variables

The highest contribution value of 4.8% for forest fire disturbance was predicted for Quercus, followed by 2% for Rhododendron, 1.9% for Cedrus and 1.6% for Pinus. Temperature seasonality was the most significant factor in all predictions for all four indicator species (Fig. 6). Minimum temperature of the coldest week was the second ranked parameter and its effect was most prominent with-wildfire. A minor contribution was predicted

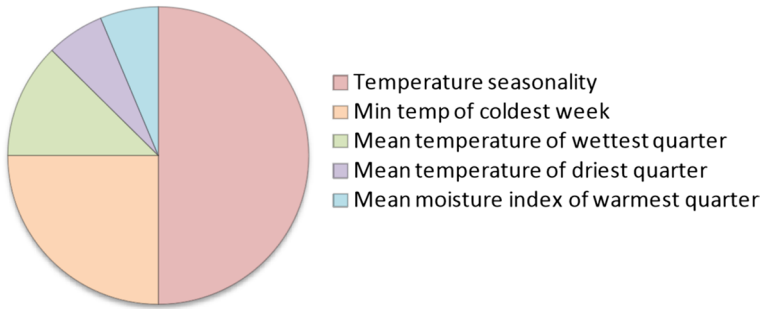


Fig. 6 Contribution of climate variables in the future distribution of indicator species

for three variables, viz. mean temperature of wettest quarter, mean temperature of driest quarter, and mean moisture index of wettest quarter.

Discussion and conclusions

Increasing frequency of wildfires in recent years is posing a threat to the biodiversity of the study area, which compelled us to study the impacts of wildfires by including them in the species distribution models. Predictions of the response of biodiversity to climate change alert researchers and policy makers to potential future risks and can support the development of proactive strategies to reduce impacts of climate change on biodiversity (Bellard et al. 2012). Despite uncertainties, our results illustrate the potential importance and the likely direction of effects climate change. From a conservation point of view, a proportion of Himalayan flora could become vulnerable to effects of wildfires. *P. roxburghii* showed the largest changes in distribution range, while *R. arboreum* showed the least shift. Large areas of the present distribution of four indicator species were predicted to shift in northerly and north-easterly directions under future climate change. These results are in line with those of Chitale et al. (2014), where they observed vast change in the species distribution of endemic plants in the Himalayan biodiversity hotspot in India. Nonetheless, owing to their range of habitats and adaptability the response of each indicator species differed from that of the others.

Our results coincide with the results from recent studies, which reported an upward shift of plants in western Himalaya owing to high rates of warming. Our results coincide with the direction of observations made by Singh et al. (2012), although the magnitude of the risks we predict is lower: We predict the highest shift in distribution range of indicator species, while Singh et al. (2012) observed a tree line shift of approximately 400 m from year 1976 to 2010. Bharti et al. (2011) predicted forest canopy increase devoid of timberline shift, whereas Telwala et al. (2013) observed shifts in 87% of endemic species in the eastern Himalaya as compared to 19th century field sampling records. An apparent shift of range along the valleys in our study area could be linked to higher moisture levels along the river channels in the valleys. Panigrahy et al. (2010) reported vegetation ingression in snowmelt regions in Central Himalaya. Matin et al. (2012) observed shift in projected distribution of *Poa annua* and *Medicago sativa* towards the valleys in the western Himalayas. Chitale and Behera (2012) predicted shift in the range of *Shorea robusta* towards east and northeast India in response to moisture availability in the eastern part of the country.

Projecting future changes in the distribution of endemic flora is a crucial step towards adapting to the impacts of climate change on biodiversity (Araujo and Rahbek 2006). The differences in the distribution ranges of the four indicator species could be attributed to the local disturbance factors, species' response to changes in climate, and the ability of species to disperse and establish themselves in new habitat. The rate of change in tropical forests would be higher than in temperate and subtropical ecosystems due to narrow ranges of temperature tolerance among the two latter types. Predictions of potential distribution of the species in this study could help in developing better conservation strategies for monitoring and managing vulnerable flora of Himalayan biodiversity hotspot, by providing an account on impacts of climate change on future distribution of plants.

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