Environmental Science and Pollution Research (2022) 29:61579–61593
https://doi.org/10.1007/s11356-021-15624-5

ECOSYSTEMS FOR FUTURE GENERATIONS

# Predicting the distributional range shifts of *Rhizocarpon geographicum* (L.) DC. in Indian Himalayan Region under future climate scenarios

Devendra Kumar[1] · Aseesh Pandey[1] · Sandeep Rawat[1] · Mayank Joshi[1] · Rajesh Bajpai[2] · Dalip Kumar Upreti[2] · Surendra Pratap Singh[3]

Received: 26 May 2021 / Accepted: 20 July 2021 / Published online: 5 August 2021


## Abstract

Himalaya, the highest mountain system in the world and house of important biodiversity hotspot, is sensitive to projected warming by climate change. *Rhizocarpon geographicum* (map lichen), a crustose lichen, grows in high mountain ranges, is a potential indicator species of climate change. In the present study, MaxEnt species distribution modeling algorithm was used to predict the suitable habitat for *R. geographicum* in current and future climate scenarios. Nineteen bioclimatic variables from WorldClim database, along with elevation, were used to predict the current distribution and three representative concentration pathway (RCP) scenarios by integrating three general circulation models (GCMs) for future distribution of species covering years 2050 and 2070. Furthermore, we performed change analysis to identify the precise difference between the current and future distribution of suitable areas of the species for delineating habitat range expansion (gain), habitat contraction (loss), and stable habitats. The final ensemble model obtained had average test value 0.968, and its predicted ~ 27.5% of the geographical area in the Indian Himalayan Region is presently climatically suitable for the species. The predicted highly suitable area for *R. geographicum* is observed to be declining in Northwestern Himalaya, and it is shifting towards the higher elevation areas of the Eastern Himalaya. The projected distribution in future under the RCP scenarios (RCP 4.5, 6.0, and 8.5) showed the range expansion towards higher elevations, and it is more pronounced for the extreme future scenarios (RCP 8.5) than for the moderate and intermediate climate scenarios (RCP 4.5 and RCP 6.0). However, assuming that species can migrate to previously unoccupied areas, the model forecasts a habitat loss of 10.86–16.51% for *R. geographicum*, which is expected due to increase in mean annual temperature by 1.5–3.7 °C. The predictive MaxEnt modeling approach for mapping lichen will contribute significantly to the understanding of the impact of climate change in Himalayan ecosystems with wide implications for drawing suitable conservation plans and to take adaptation and mitigation measures.

**Keywords** *Rhizocarpon geographicum* · Himalaya · Climate change · Habitat loss · Niche shifts · Species distribution modeling · Lichen

Responsible Editor: Philippe Garrigues

✉ Devendra Kumar
devendrawii@gmail.com

Aseesh Pandey
draseeshpandey@gmail.com

Sandeep Rawat
sandeep_rawat15@rediffmail.com

Mayank Joshi
mayank.geo@gmail.com

Rajesh Bajpai
bajpaienviro@gmail.com

Dalip Kumar Upreti
upretidknbri@gmail.com

Surendra Pratap Singh
spsecology@gmail.com

[1] G.B. Pant National Institute of Himalayan Environment (NIHE), Sikkim Regional Centre, Gangtok, Sikkim, India

[2] Lichenology Lab, CSIR-National Botanical Research Institute, Lucknow, Uttar Pradesh 226001, India

[3] Central Himalayan Environment Association (CHEA), 06-Waldorf Compound, Mallital, Nainital, Uttarakhand 263 001, India

## Introduction

Climate change not only alters the natural ecosystems but also affects each and every species on the earth to a lesser or greater extent (Walther et al. 2002). Habitat reduction and shifting, physiological and behavioral changes in biota, and extinction of species have been observed as impacts of global climate change (Forrest et al. 2012; Bajpai et al. 2016a). Species are shifting their elevation ranges, latitudinal distribution, and phenologies in response to changing climate (Lavorel and Ganier 2002; Wilson et al. 2005; Hamid et al. 2019; Kumar et al. 2019). The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) predicted that global climate warming will be continued and the average temperature on the earth will be increased by 0.3–4.5 °C through the end of the twenty-first century (relative to the 1986–2005 baselines) (Stocker et al. 2014). To mitigate the effects of climate change on forest ecosystems and their functioning, we can effectively target conservation strategies by modeling species distribution to identify the suitable habitat areas where key species exist or probability of existence. For effective modeling of species, detailed information about the ecology and spatial distribution pattern of species is a prerequisite. Predicting critical suitable habitat availability will also influence better understanding of ecological systems and the distribution patterns of genetic variation within species (Wang et al. 2012).

Predictive models are widely used powerful tools to obtain an initial understanding of species distribution in response to climate change (Thuiller et al. 2006; Pereira et al. 2010). The ecological niche modeling (ENM) tool is commonly used in predicting the geographic range of species, using presence records and environmental predictors which are assumed to influence its distribution (Raxworthy et al. 2003; Anderson and Martinez-Meyer 2004; Elith and Leathwick 2009; Elith et al. 2011; Peterson et al. 2011; Kong et al. 2021). In recent years, ENM using maximum entropy model (MaxEnt) has emerged as a useful tool in modeling of rare and economically important plant species, including even those with a narrow range and only few presence records (Phillips et al. 2006; Pearson et al. 2007; Elith et al. 2011; Garcia et al. 2013; Hamid et al. 2019; Kumar et al. 2019).

Lichens are among the most vulnerable organisms to changes in environment and climate, induced by both natural and anthropogenic factors, while this sensitivity is mostly due to their low physiological tolerance (Kukwa and Kolanowska 2016; Żołkoś et al. 2013; Wolseley et al. 2006). Lichens (lichenized fungi) are an artificial group of various, distantly related fungal lineages that comprise a mutualistic dependence on a photoautotrophic partner (Miądlikowska et al. 2014). They are poikilohydric in nature and lack vascular system thus cannot regulate their water content actively and absorb water and nutrients passively from their surrounding environment (Green et al. 2011). Because of this, lichens are particularly sensitive to climate changes and air pollution (Pinho et al. 2011; Branquinho et al. 2015). Lichens occur in a variety of land ecosystems from Antarctica to desert and up to the highest mountain (Nash III et al. 1990). Their mechanisms of growth and physiology are significantly regulated by moisture and temperature. These biological and eco-physical barriers make them ideal organisms for examining the effects of climate change.

The Himalaya is experiencing warming at a higher rate than the global average (three times higher, 0.06 °C/year; Shrestha et al. 2012). The Hindu Kush Himalaya Assessment report indicated that if the average global warming will be limited to 1.5 °C above the pre-industrial period, this region will warm by 1.80 ± 0.40 °C (Krishnan et al. 2019). The region represents a rich repository of biodiversity and thus designated as one of the 36 global biodiversity hostspots (Mittermeier et al. 2011). Considering the rich biodiversity, endemism, and higher sensitivity towards climate change, studies are sparse on the species responses to changing climate (Saran et al. 2010; Kumar 2012; Forrest et al. 2012; Telwala et al. 2013; Shrestha and Bawa 2014; Manish et al. 2016; Hamid et al. 2019; Kumar et al. 2019). Because of its distinct evolutionary history and rich species diversity, the Himalayan region warrants more understanding on species responses and ecosystem functioning with regard to climate change (Pandit and Babu 1998; Pandit et al. 2007).

In earlier studies, particularly in Europe and North America, the ENM tools have been used to test the distribution patterns (Szczepańska et al. 2015), taxonomic research on *Fuscopannaria confusa* (Carlsen et al. 2012), local conservation planning (Cameron et al. 2011; Binder and Ellis 2008), and influence of climate change on the future distribution of several lichen species (Ellis et al. 2007a, 2007b; Ellis et al. 2014; Allen and Lendemer 2016; Kukwa and Kolanowska 2016; Rubio-Salcedo et al. 2017; Ellis 2019). Using ensemble modeling algorithm, the current and the future distribution of *Rhizocarpon geographicum* (Map Lichen) were mapped across the Indian Himalayan Region (IHR) in view of climate change. *R. geographicum* is a crustose lichen, which grows on the exposed rocks surface in higher Himalayan mountains and is well-suited as climate change indicator species in lichenometry (Armstrong 2004). To date, no attempt has been made to understand the distribution modeling of *R. geographicum* at regional or global scale. The objective of the present study aimed (i) to determine the important climatic variables which enhance habitat prediction accuracy of *R. geographicum* in current climatic condition, (ii) to assess the potential distribution of *R. geographicum* under the current and future climatic conditions, (iii) to determine the susceptibility of *R. geographicum* to the possible future range contraction/expansion, and (iv) to propose conservation strategies and management options under different scenarios.

## Material and methods

### Study area

The study was carried out in the IHR which comprises four states (viz., Himachal Pradesh, Uttarakhand, Sikkim, and Arunachal Pradesh) and two Union Territories (viz., Jammu and Kashmir and Ladakh), covering approximately 12% of total geographical area of India (Fig. 1). Physiographically, the region has four zones from south to north, viz., the shivaliks, the lesser Himalaya, the greater Himalaya, and Trans-Himalaya zones. The mountain ranges in IHR are distributed up to an altitude of 8586 m and extending 8° (26° to 34° N) in latitude and 28° (69° to 97° E) in longitude. This huge mountain ranges of IHR have been historically divided into two eco-sensitive regions: the Eastern Himalaya, which covers Arunachal Pradesh and Sikkim states of north-eastern region of India, and the Western Himalaya, covering the Uttarakhand, Himachal Pradesh, Jammu and Kashmir, and Ladakh.

According to the State of Forest Report-2019, forest cover in the IHR is ~41% of the total geographical area out of which 16.9% area is under very dense forest cover, 45.4% under moderate forest cover, and the remaining 37.7% under open forest category (ISFR 2019). The Himalayan forests are extensive and diverse and they differ significantly from both tropical and temperate forests with respect to structure, growth cycle and function as well as in terms of ecosystem processes (Zobel and Singh 1997). Forest vegetation in the region ranges from tropical moist-deciduous forests in the foothills to alpine meadows above treeline (Champion and Seth 1968). About 6% of Indian human population lives in the IHR. The growing population and consequent anthropogenic pressures in the region have exerted considerable pressure on various ecosystems (Badola and Hussain 2003). Further, changing land use patterns, unsustainable use of natural resources, and unplanned infrastructure developments have led to habitat loss, ecological degradation, and forest fragmentation resulting to changes in species range, diversity, and numbers, and their local extinctions. In addition to this, climate change–induced impacts are predicted to affect the critical ecosystem goods and services provided by the IHR.

### Target species

*Rhizocarpon geographicum* (L.) DC. (the map lichen; Family, Rhizocarpaceae) is a crustose lichen, which grows on exposed rock surface in higher mountain region (Fig. 2). This lichen species is broadly distributed in the North American range, sub-Antarctic islands, Antarctic Peninsula, Andes of Peru, Colombia, and South Asia (Caseldine and Baker 1998). In India it is distributed throughout the Himalayan region (Jammu and Kashmir, Himachal Pradesh, Uttarakhand, Sikkim, and Arunachal Pradesh) at 3000–4300-m altitude (Bajpai et al. 2016b). It grows at substantially lower rates than other foliose and crustose lichen, especially in arctic and alpine environment (Armstrong 2005). Having circular or roughly circular yellow green thalli, this lichen species is widely used in determining the relative age of deposits, e.g., moraine systems, thus revealing evidence of glacial advances, through lichenometry (Beschel 1973; Armstrong 2004). Lichenometry is the geomorphic method of geochronologic dating that uses lichen growth to determine the age of exposed

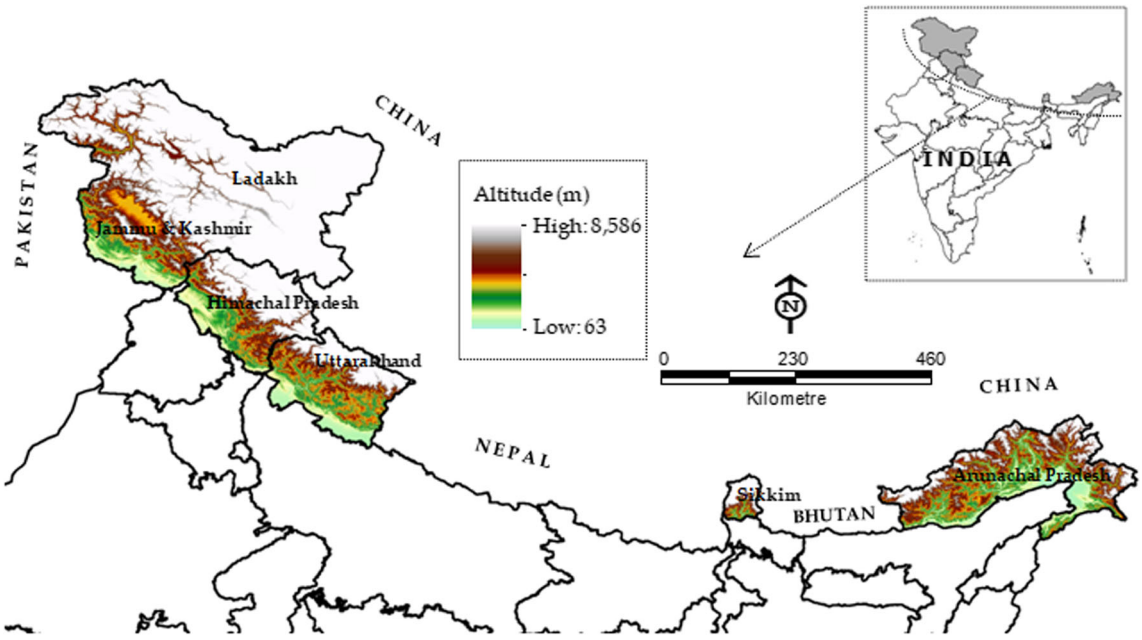


**Fig. 1** Map of study area (Indian Himalayan Region) showing the elevation gradients


**Fig. 2** **a** Target species (*Rhizocarpon geographicum* (L.) DC.) and **b** its natural habitat in Indian Himalayan Region

rock, based on a presumed specific rate of increase in radial size of thalli over the time.

## Species presence data

In total 159 species presence records of *R. geographicum* were incorporated in this investigation (Supplementary Material; Table S1). This includes 117 records from Lichen herbaria of CSIR-National Botanical Research Institute (NBRI), Lucknow, India, and 42 records from field survey in different natural habitats across IHR. The point's record from each herbarium specimens was transformed into geographical co-ordinates using Google Earth and ArcGIS (version 10.3) software.

## Environmental predictors

A total of 19 bioclimatic variables (Hijmans et al. 2005) from WorldClim database (http://www.worldclim.org) at a resolution of approximately 1 $km^2$ were used for distribution modeling of *R. geographicum*. The variables derived from monthly mean temperature and precipitation data (Table 1) had a high conformity rate in species distribution modeling, even for those having few distribution records (Pearson and Dawson 2003; Khanum et al. 2013; Hamid et al. 2019; Kumar et al. 2019). In addition to 19 bioclimatic variables, topographic variable (altitude) of 30 arc second (approx. ~ 1 km) spatial resolution was utilized as additional predictor variables for modeling current potential distribution of *R. geographicum*. The future climate data from IPCC 5th assessment for the

**Table 1** Percentage contribution and permutation importance of the environmental variables in the MaxEnt models for *R. geographicum*; values shown here are averages over twenty replicate runs

| Environmental variables | Code | Unit | Percentage contribution | Permutation importance |
|---|---|---|---|---|
| **Annual mean temperature** | **Bio1** | **°C** | **37.8** | **86.6** |
| **Mean diurnal range temperature** | **Bio2** | **°C** | **0.9** | **2.5** |
| **Isothermality (Bio2/Bio7)*100** | **Bio3** | | **2.9** | **1.3** |
| **Temperature seasonality** | **Bio4** | | **7.8** | **0.9** |
| Maximum temp of warmest month | Bio5 | °C | - | - |
| Minimum temperature of coldest month | Bio6 | °C | - | - |
| Temperature annual range | Bio7 | °C | - | - |
| **Mean temperature of wettest quarter** | **Bio8** | **°C** | **8.8** | **0.7** |
| Mean temperature of driest quarter | Bio9 | °C | - | - |
| Mean temperature of warmest quarter | Bio10 | °C | - | - |
| Mean temperature of coldest quarter | Bio11 | °C | - | - |
| Annual precipitation | Bio12 | mm | - | - |
| Precipitation of wettest month | Bio13 | mm | - | - |
| **Precipitation of driest month** | **Bio14** | **mm** | **2.0** | **3.4** |
| Precipitation seasonality | Bio15 | | - | - |
| Precipitation of wettest quarter | Bio16 | mm | - | - |
| Precipitation of driest quarter | Bio17 | mm | - | - |
| Precipitation of warmest quarter | Bio18 | mm | - | - |
| Precipitation of coldest quarter | Bio19 | mm | - | - |
| **Altitude** | **Alt** | **m** | **39.7** | **4.5** |

years 2050 and 2070 were used from http://www.ccafs-climate.org/ web-source to project the future potential distribution of the target species.

For reducing the uncertainty in model prediction, we used three different global climate models (GCMs), i.e., MRI-CGCM3, CSIRO-MK3.6, and HadGEM2-CC. Each GCM was tested under future greenhouse gas concentration trajectories, called representative concentration pathways (RCPs), i.e., RCP 4.5, RCP 6.0, and RCP 8.5, for the periods 2050 and 2070. The RCP 4.5 ("intermediate stabilization pathways") was developed by Pacific Northwest National Laboratory, USA. It is relatively stable scenario in which greenhouse gases (GHG) will stabilize due to greenhouse technologies and total radiative forcing reaches 4.5 W/m$^2$ and stabilized shortly after 2100, without overshooting the long-run radiative forcing target level (Smith and Wigley 2006; Wise et al. 2009). RCP 6.0 was developed by the National Institute for Environmental Studies, Japan, and it is a stabilization scenario where total radiative forcing is stabilized after 2100 without overshoot by employment of a range of technologies and strategies for reducing GHG (Fujino et al. 2006; Hijioka et al. 2008). However, RCP 8.5 was developed by International Institute for Applied Systems Analysis, Austria, and it represents relatively extreme scenarios where GHG will continuously increase throughout 2100, at which time radiative force will reach 8.5 W/m$^2$ (Riahi et al. 2007; Meinshausen et al. 2011). For future potential distribution predictions, we ran averaging the results (ensemble approach) from the CGCM3, CSIRO-MK3, and HadGEM2-CC future climate models (Araújo and New 2007).

To reduce multi-collinearity among the 20 environmental variables, highly correlated variables were eliminated from further modeling using pair-wise Pearson's correlation coefficient ($r \geq 0.85$). This reduction of predictor variables resulted in the inclusion of seven variables for models (Supplementary Material; Table S2). These variables included annual mean temperature (Bio1), mean diurnal range temperature (Bio2), isothermality (Bio2/Bio7)*100 (Bio3), temperature seasonality (Bio4), mean temperature of wettest quarter (Bio8), precipitation of driest month (Bio14), and altitude (Alt) (Table 1).

## Predictive MaxEnt modeling

For predictive modeling, we used maximum entropy–based techniques, i.e., MaxEnt ver. 3.3.3k (http://www.cs.princeton.edu/~schapire/MaxEnt/), because of their better performance with small sample sizes relative to other modeling algorithms (Elith et al. 2011). MaxEnt program is based on maximum entropy theory and uses only presence records data for predicting species distribution (Phillips et al. 2006). The probability output response of MaxEnt devised by Phillips et al. (2006) can either be raw, logistic, or cumulative, and for this study logistic response was selected, following Phillips and Dudik (2008).

In total, twenty replicate runs were set for modeling and averaged the result. In replicate run, cross-validation technique was selected, in which samples are divided into replicate folds and each fold is used to test data. To estimates relative influence of different predictor variables, jackknife test (Pearson et al. 2007; Shcheglovitova and Anderson 2013), response curve, and relative percentage contribution of variables (Rajpoot et al. 2020; Kumar et al. 2021) were used. We used the area under ROC (receiver operating characteristics) curve (AUC) to estimates model performance and accuracy. The value of AUC ranged from 0 to 1 (Fielding and Bell 1997). An AUC value closer to 0.5 indicates that the model did not perform better than random, whereas value closer to 1.0 indicates perfect and more accurate prediction (Swets 1988). The thresholds values adopted for interpreting the AUC were as follows: 0.5–0.6, fail; 0.6–0.7, poor; 0.7–0.8, fair; 0.8–0.9, good; and 0.9–1, excellent (Lobo et al. 2008). Further, model performance was assessed based on the partial AUC metrics (Lobo et al. 2008) calculated using online NicheToolBox (http://shiny.conabio.gob.mx:3838/nichetoolb2/). The distribution of AUC ratios was plotted by executing 5% omission with 500 bootstrap iterations, followed by comparison between mean value of $AUC_{random}$ and $AUC_{partial}$ to test whether the model performed better than random predictions. For conformity of model robustness, we executed 10 percentile training presence threshold rules over a twenty replicates of model runs (Pearson et al. 2004). Other setting was set to default as the MaxEnt algorithms are already calibrated on a wide range of species datasets as suggested by Phillips and Dudik (2008).

## Analysis of habitat change

We have analyzed the suitable habitat change area for future scenarios of 2050 and 2070 years under the RCP 4.5, 6.0, and 8.5. For the habitat suitability class maps, we categorized the final logistic output of MaxEnt model into the following classes: (i) unsuitable (0.00–0.25), (ii) low suitable (0.25–0.50), (iii) medium suitable (0.50–0.75), and (iv) high suitable (0.75–1.00) in DIVA GIS (version 7.5) (Hijmans et al. 2005).

## Analysis of range contraction or expansion

By subtracting the binary map of current period with each of the future scenarios in ArcGIS (Version 10.3), climatic range shift maps of *R. geographicum* were generated for 2050 and 2070 years under RCP 4.5, 6.0, and 8.0. Each maps represent the following classes: (i) stable/no-change (predicted areas remain to suitable), (ii) unsuitable, (iii) lost (areas not predicted to remain suitable in future/range contraction), and (iv)

gained habitats (areas that are predicted to be suitable in future but currently not suitable/range expansion).

## Results

### Model performance

The model calibration test for *R. geographicum* yielded highly satisfactory results, evident by average training and test AUC values of 0.984 ± 0.002 and 0.968 ± 0.030, respectively. The average partial AUC value at 5% omission with 500 bootstrap iterations was 0.9635±0.012 (Fig. 3). All the tests for model performance showed that the MaxEnt model for *R. geographicum* exhibit excellent consistency and represents more defined and restricted ecological niche in the study area with high accuracy.

### Influencing predictor variables

Amongst the seven selected environmental predictors, altitude (alt) and annual mean temperature (Bio1) together contributed 77.5% to the model and appeared as most influential variables for current potential distribution of *R. geographicum* (Table 1). Precipitation of driest month (Bio14) and mean diurnal range temperature (Bio2) made the lowest contribution to the predictive model. Considering the permutation importance, annual mean temperature (Bio1) had the maximum influence on model and contributed to 86.6%, followed by altitude (alt), i.e., 4.5% (Table 1). The climatic profiles (based on the occurrence records of species: minimum, maximum, and mean values) of 20 environmental variables for the species under investigation are presented in Table S3 (Supplementary Material).

The response curves showed the changes in the logistic prediction when each predictor variable changed by keeping all other variables at their average sample value. The response curve of *R. geographicum* showed that the elevation (alt) influenced the habitat suitability area at certain range only (Fig. 4a), and a bell-shaped distribution curve was observed for annual mean temperature (Bio1) (Fig. 4b). Mean temperature of wettest quarter (Bio8) and temperature seasonality (Bio4) negatively influenced the logistic prediction (Fig. 4c,d). The jackknife test showed that the annual mean temperature (Bio1) and altitude (alt) are the main factors influencing the distribution pattern of *R. geographicum* and showed highest training gain (Fig. 4e).

### Potential current prediction

By undertaking visual inspection of the potential current prediction of *R. geographicum* based on occurrence records, it is clear that the Eastern Himalayan region possesses highly suitable habitat (red) distributed through Sikkim to Arunachal Pradesh state of IHR, whereas in Western Himalayan region, Uttarakhand and Himachal Pradesh possess highly suitable habitat classes (Fig. 5a). The current suitable habitats of *R. geographicum* cover 27.7% of the total geographical area of IHR and are confined mainly to areas between 3000 and 4300 m. Such habitats occur throughout the Eastern Himalayan region and Western Himalayan region, except the westernmost part (Jammu & Kashmir and Ladakh) (Fig. 6a).

### Habitat suitability classes under current and future climatic conditions

During the future climate change scenarios (2050 and 2070), some of the areas which are currently less suitable for *R. geographicum* will become suitable, and at the same time, some areas which are modeled to be highly suitable in the current climatic condition will become less suitable. In the Eastern Himalayan region, the highly suitable habitat area (red) is predicted to increase and shift towards higher elevations in future climatic scenarios (Fig. 5). In the Western Himalayan region, the

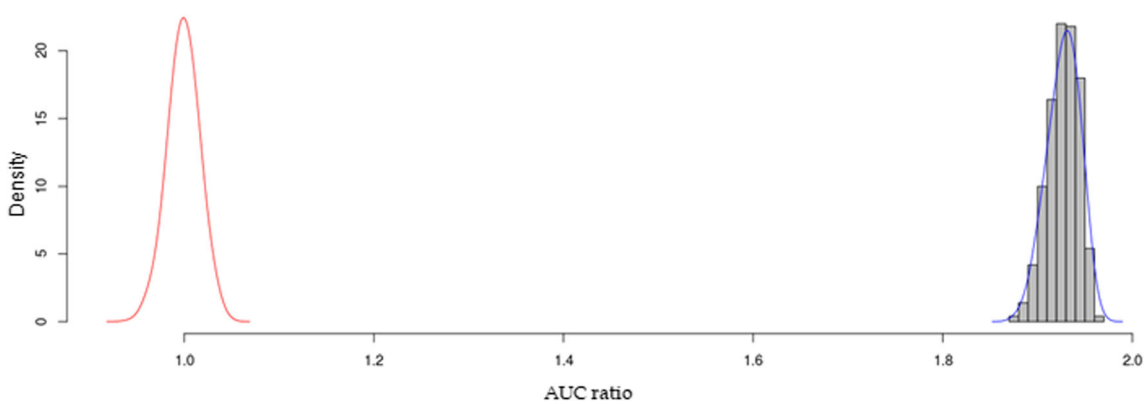


**Fig. 3** Partial area under curve (AUC) distribution for *Rhizocarpon geographicum* generated by executing 5% omission with 500 bootstrap iterations in the receiver operating characteristic (ROC) space. Red curve represents the distribution of AUC ratios for random models, while the blue curve along with shaded bars show the frequency distribution of the ratios between AUC from model prediction and $AUC_{random}$

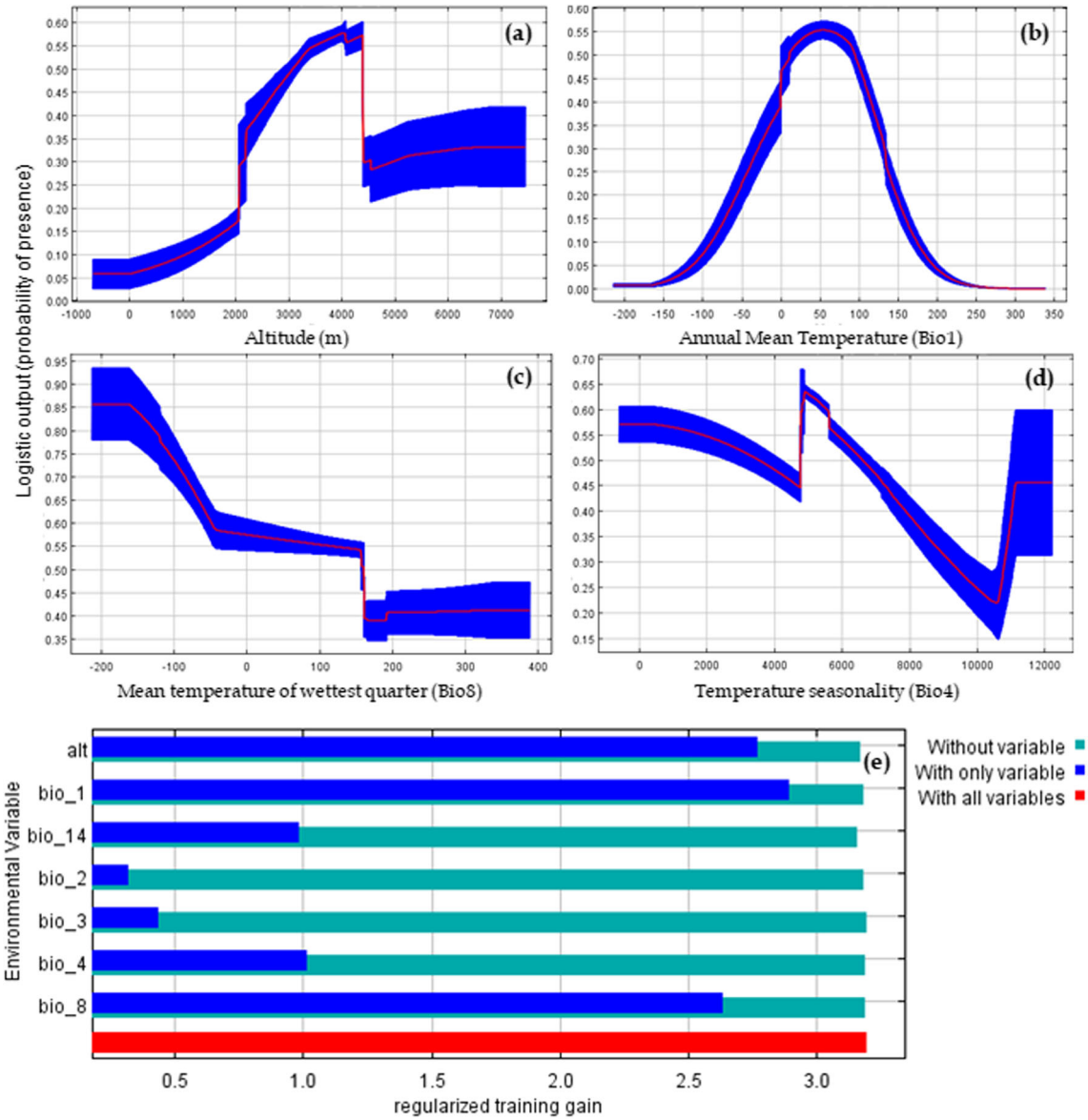


**Fig. 4** **a**–**d** Response curves showing relationships between probability of species presence and climatic variables. **e** Jackknife regularized training gain, showing the relative predictive power of bioclimatic variable (values shown are average of twenty replicate runs)

loss of suitable habitat area is predicted more for all habitat classes, i.e., low (light blue), moderate (dark blue), and high (red), for the future climate change scenarios (Fig. 5).

Our analysis showed that in 2050, there will be a decrease in highly suitable habitat area (showed in red color) by − 1.69% (RCP 6.0) to − 5.50% (RCP 8.5). Similarly, the moderately suitable habitat area (dark blue color) showed considerable loss in suitable area in all scenarios, i.e., RCP 4.5, 6.0, and 8.5 by − 2.13%, − 4.48%, and − 0.50%, respectively. The low suitable habitat area (light blue) showed marginal decrease by − 1.39% in RCP 6.0 and a marginal increase of 0.83% and 0.25% in RCP 4.5 and RCP 8.5, respectively. Similarly, in 2070, it is expected that there will be a considerable decrease in highly suitable habitat area (red), by − 4.10% and − 6.46% under RCP 4.5 and RCP 8.5 and marginal decrease by − 1.48% under the RCP 6.0. The moderately suitable habitat area (dark blue) will also be lost by − 9.45%, − 2.71% and − 3.52% for RCP 4.5, 6.0, and 8.5, respectively. The low suitable habitat area (light blue) showed very small gain in suitable area by 0.11% for RCP 6.0 and considerable loss in suitable area by − 4.46% and − 2.77% for RCP 4.5 and RCP 8.5, respectively. The unsuitable area (white) showed an increase for all future scenarios (RCP 4.5, 6.0 and 8.5) over the years 2050 and 2070 (Table 2 and Fig. 5).

## Range contraction or expansion

Area with suitable climatic conditions for *R. geographicum* is predicted to decline by the 2050s and the 2070s under all RCP scenarios. The averaged future prediction from three GCMs under the RCP 4.5 by year 2050 showed the loss of 17.03%

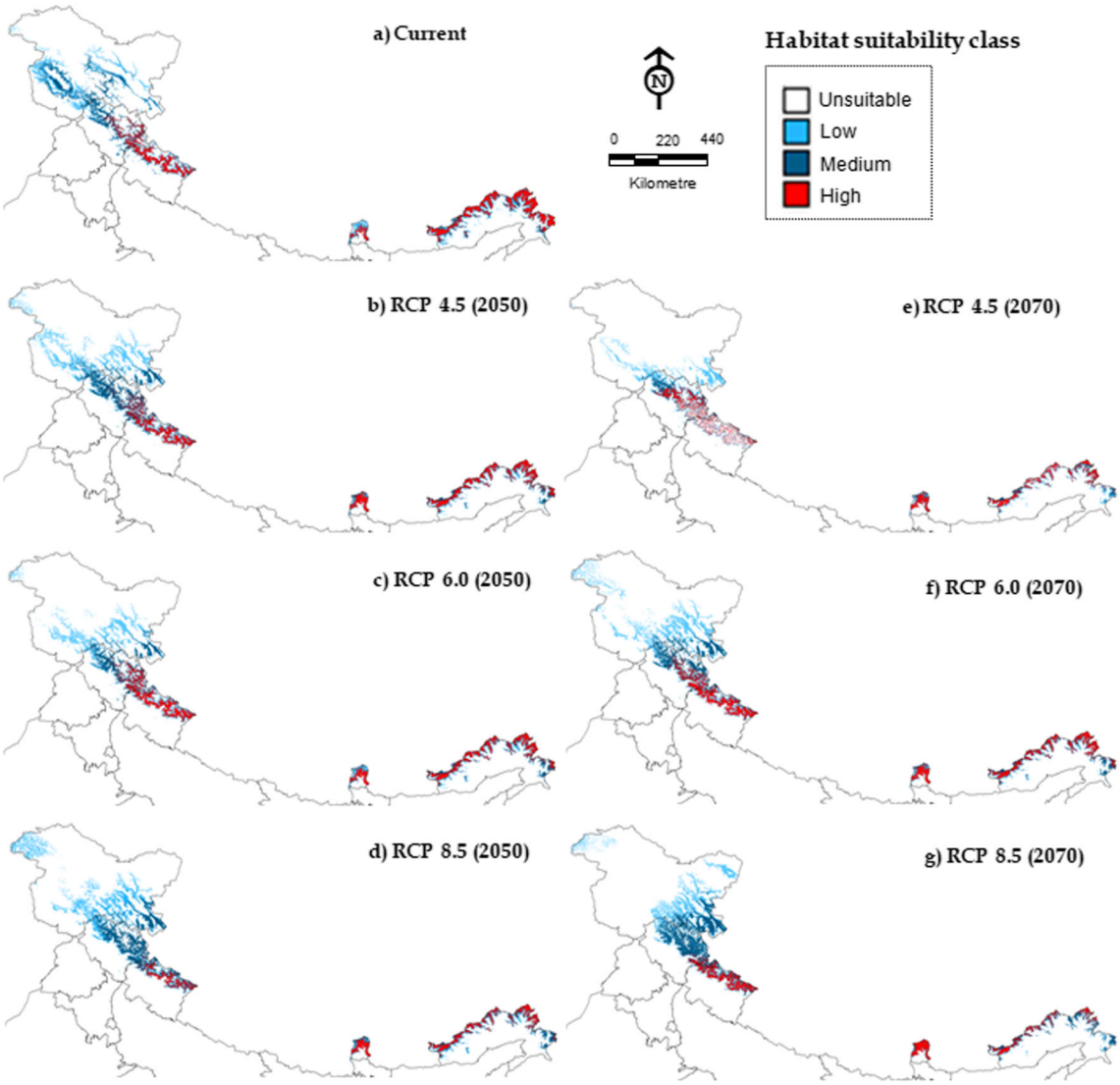


**Fig. 5** Habitat suitability map for *R. geographicum* developed for current and future climate change scenarios for year 2050 and 2070 (white = not suitable, light blue = low suitable, dark blue = medium suitable and red highly suitable)

(51,322 km$^2$), suitable area (indicated in dark green color/ no change/ stable), and an increase by year 2070 (56,822 km$^2$; 18.66%), from the current climatic suitable value as 27.96% (84,252 km$^2$) (Table 3; Fig. 6). In RCP 6.0, the average future prediction for the year 2050 showed loss of suitable habitat area (49,791 km$^2$; 16.52%), and further loss in suitable habitat area (46,763 km$^2$; 15.53%) is predicted for the year 2070 (Table 3; Fig. 6). Whereas in higher scenarios (RCP 8.5) the loss of suitable habitat area predicted was greater than both the RCPs (4.5 and 6.0), and the predicted loss in suitable habitat area is from 14.11% (42,518 km$^2$) to 11.38% (34,305km$^2$) for the year 2050 and 2070 respectively (Table 3; Fig. 6). The loss in suitable habitat area in average model of RCP 4.5 and 6.0 was predicted to occur in patches in eastern Himalaya region (Sikkim and Arunachal Pradesh) and in large continuous blocks in Western Himalaya (Jammu and Kashmir, Ladakh, Himachal Pradesh and Uttarakhand) ([Fig. 6).

It is estimated that in 2050 there will be a huge range contraction (area indicated in red color) in current suitable area of *R. geographicum* towards north-west side of Western Himalaya (Jammu and Kashmir). Conversely, there will be range expansion (area showed in purple color) in the habitat by 15,394 km$^2$ (5.11%) in RCP 6.0 to 23,166 km$^2$ (7.69%) in RCP 8.5, towards the northern side of Eastern Himalaya (Sikkim and Arunachal Pradesh) and north-eastern side of Western Himalaya (Himachal Pradesh and Uttarakhand). The unsuitable area (area indicated in light green color) varied from 1,94,144 km$^2$ (64.42%) to 2,01,916 km$^2$ (67.0%). Likewise, by 2070, range contraction (red) of current suitable area for *R. geographicum* varied from 27,430 km$^2$ (9.10%) under RCP 4.5 to 49,747 km$^2$ (16.51%) under RCP 8.5 in lower elevation zone of Eastern and Western Himalayan regions, and there will be a range expansion (purple) in suitable habitat from 24,310 km$^2$ (8.07%) in RCP 6.0 to 39,856 km$^2$ (8.50%) in RCP 8.5, towards the north-eastern parts of Western Himalayan states

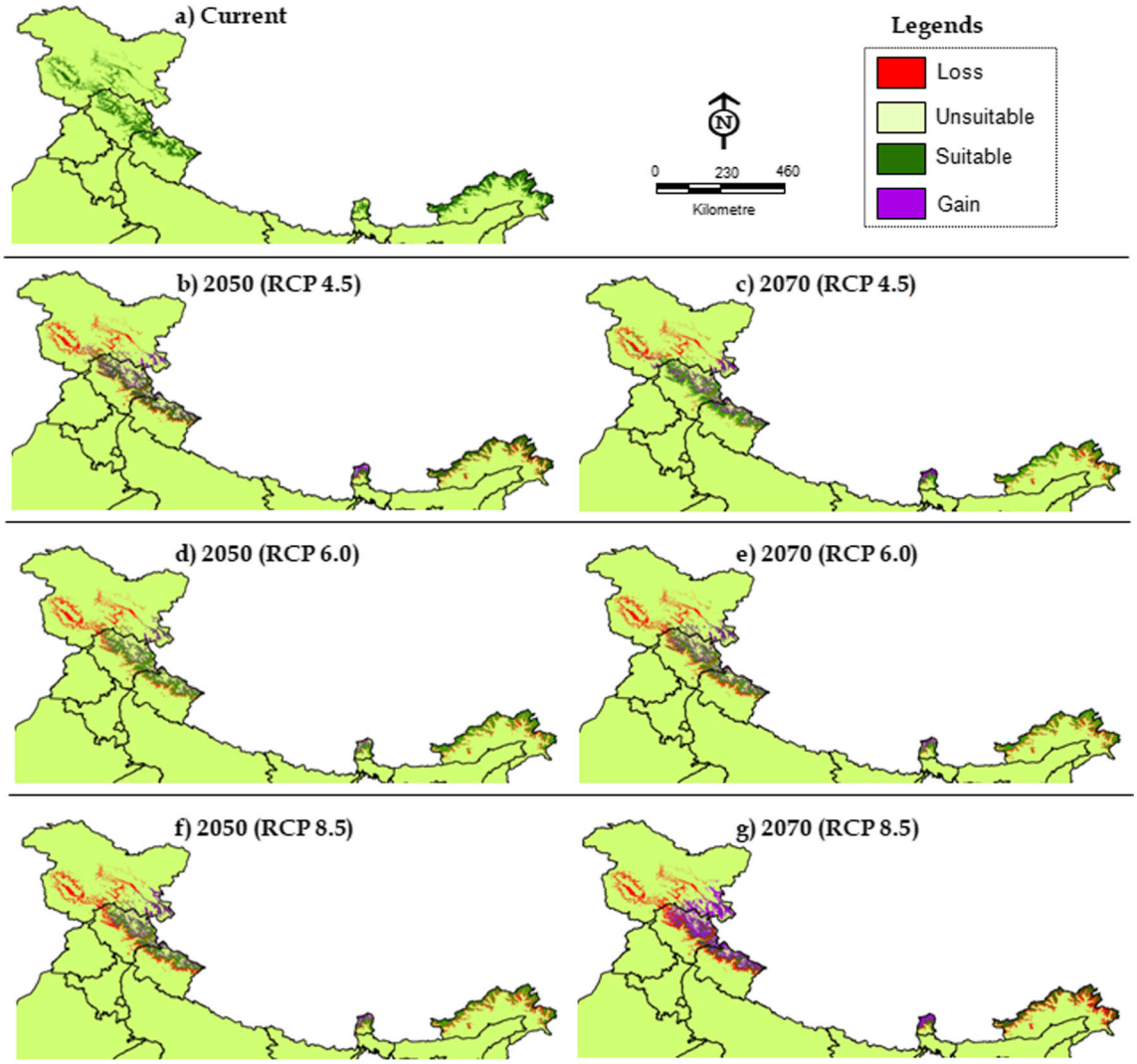


**Fig. 6** Climatic range shifts of *R. geographicum* under different RCP scenarios for 2050 and 2070 (dark green color indicates suitable/no change; red, loss; purple, gain; and light green, unsuitable)

(Jammu & Kashmir, Ladhakh Himachal Pradesh and Uttarakhand). The unsuitable area (light green) by 2070 also varied from 1,77,454 $km^2$ (58.88%) in RCP 6.0 to 1,93,000 $km^2$ (64.04%) in RCP 8.5. In summary both scenarios (2050 and 2070) showed similar trends for range contraction and expansion, and collectively the range expansion/contraction reached peak under the RCP 8.5 scenario for the year 2070 (Table 3 and Fig. 6).

## Discussion

ENM tools have become increasingly appreciable in ecological and bio-geographical research globally (Guisan and Zimmermann 2000), mostly because ecologists need ways of rapidly assessing potential distribution and impact of climate change on large numbers of species, with only few

**Table 2** Percentage change in habitat suitability class area for *R. geographicum* under different RCP scenarios for 2050 and 2070

| Logistic range | Habitat suitability classes | Current RCP 4.5 | | Current RCP 6.0 | | Current RCP 8.5 | |
|---|---|---|---|---|---|---|---|
| | | 2050 | 2070 | 2050 | 2070 | 2050 | 2070 |
| 0.00–0.25 | Unsuitable | − 3.42 | − 18.01 | − 7.56 | − 4.08 | − 5.75 | − 12.30 |
| 0.25–0.50 | Low | − 0.83 | 4.46 | 1.39 | − 0.11 | − 0.25 | 2.77 |
| 0.50–0.75 | Medium | 2.13 | 9.45 | 4.48 | 2.71 | 0.50 | 3.52 |
| 0.75–1.00 | High | 2.12 | 4.10 | 1.69 | 1.48 | 5.50 | 6.46 |

**Table 3** Predicted suitable habitat area change (range expansion and range contraction) for *R. geographicum* under different RCPs for 2050 and 2070

| Classes | Area (km$^2$) | | | | | | | Area (%) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Current | RCP 4.5 | | RCP 6.0 | | RCP 8.5 | | Current | RCP 4.5 | | RCP 6.0 | | RCP 8.5 | |
| | | 2050 | 2070 | 2050 | 2070 | 2050 | 2070 | | 2050 | 2070 | 2050 | 2070 | 2050 | 2070 |
| Suitable/no change | 84,252 | 51,322 | 56,822 | 49,791 | 46,793 | 42,518 | 34,305 | 27.96 | 17.03 | 18.86 | 16.52 | 15.53 | 14.11 | 11.38 |
| Loss | | 32,730 | 27,430 | 34,261 | 37,259 | 41,534 | 49,747 | | 10.86 | 9.1 | 11.37 | 12.36 | 13.78 | 16.51 |
| Gain | | 19,635 | 25,752 | 15,394 | 24,310 | 23,166 | 39,856 | | 6.52 | 8.55 | 5.11 | 8.07 | 7.69 | 13.23 |
| Unsuitable | 2,17,110 | 1,97,675 | 1,91,358 | 2,01,916 | 1,93,000 | 1,94,144 | 1,77,454 | 72.04 | 65.59 | 63.5 | 67 | 64.04 | 64.42 | 58.88 |

distribution records (Araújo and Rahbek 2006). Several critical opinions on ENM analysis have been presented over the years, and MaxEnt seems to be the most reliable application for modeling species distribution (Bradie and Leung 2016), and its usefulness was also tested in the case of rare species (Kumar and Stohlgren 2009; Rebelo and Jones 2010). In the present investigation, the MaxEnt modeling result suggests that the suitable habitat area for *R. geographicum* would shrink under the predicted levels of climate change. The MaxEnt model performed better than random, with high satisfactory mean test AUC value. MaxEnt predicted the loss of suitable habitat area more in Western Himalayan region than in Eastern Himalayan region. It was also predicted that the species may shift upward (i.e., more than 4000-m-high elevated zones), mostly in Western Himalayan region (Uttarakhand, Himachal Pradesh, and Jammu and Kashmir) (Fig. 6).

Field observations suggest the *R. geographicum* is highly dependent on local seasonal climate and generally colonized on the exposed rock surfaces in treeline ecotones to alpine meadows between 3000 and 3900 m in Western Himalaya and 3500 and 4400 in Eastern Himalaya. Among the temperature-related climatic variables, the mean annual temperature, mean temperature of wettest quarter, and temperature seasonality have shown significant contribution in model prediction. Currently, *R. geographicum* is more abundant (highly suitable habitat area) towards the Eastern Himalayan region, possibly because of low mean temperature of wettest quarter and higher mean temperature of warmest month. The low winter temperature at treeline elevations in Western Himalayan region seems to restrict its abundance (Sharma et al. 2009; Ranjitkar et al. 2014; Tewari et al. 2017).

The slow growth rate and longevity of *Rhizocarpon* species are valuable tools to estimate the exposure age of rock surface, i.e., in lichenometry (Locke et al. 1979; Innes 1985; Mathews 1994; Benedict 2009; Bajpai et al. 2016b). Thus, considering the importance of *R. geographicum* in lichenometry, the present investigation of MaxEnt model showed that the predicted suitable habitat area under the current climate condition would become unsuitable in the predicted future climate change scenarios, indicating direct evidence for declining or melting of glacier/ice cover in future climate change scenarios.

Considering climate sensitivity of the species, the seasonality (such as temperature, rainfall, and humidity) exposure to it leads to a regular, periodic changes in the growth of thalli and availability of resources (Armstrong 2006; Armstrong 2011). Innes (1985) found that close to snow patches, the thalli of *R. geographicum* were smaller than expected. Similarly, Pitman (1973) observed that the thallus diameter increased away from the center of snow patches due to a reduced growing season and ground instability. All of these factors are known to combine in trigging the morphological and physiological changes in species (Armstrong 2011). Then, the species may be capable of adapting to future climate condition through physiological changes or through adaptation to microclimatic conditions responsible for its survival in natural conditions.

In the current investigation, the MaxEnt model output of *R. geographicum* showed the range expansion of suitable habitat towards higher elevation areas of Himalaya in future climate scenarios, which may be possible through adaption towards the changes in local climatic condition. These range expansions were generally more pronounced for the extreme future scenarios (RCP 8.5) than for the moderate and intermediate climate scenarios (RCP 4.5 and RCP 6.0). Rubio-Salcedo et al. 2017) predicted similar results of adaption and range expansion for forty one lichen species in Iberian Peninsula in response to the climate change, using ensemble climatic modeling approach, whereas Ellis et al. (2014) projected the suitable climate space for 382 epiphytic lichen species in Brittan and showed that 38% of the species losing and 62% are gaining the suitable habitat area, by 2080. Furthermore, a study across twenty-six mountains in Switzerland demonstrated upward (towards the higher elevation) range extension of the alpine vegetation (Pauli et al. 1996). A similar study by Moiseev and Shiyatov (2003) showed the upward shift of treeline in Siberia. Several studies mainly showed the significant loss of suitable habitat under climate change scenarios for many lichen species in various geographical regions (Hauck 2009; Binder and Ellis 2008; Lang et al. 2012; Ellis 2013; Allen and Lendemer 2016; Rubio-Salcedo et al. 2017; Ellis 2019). Recently, Allen and Lendemer (2016) and Devkota et al. (2019) have shown that

climate change poses a significant threat to montane lichen species in higher elevation area. Devkota et al. (2019) predicted the loss of suitable habitat for endemic lichen *Lobaria pindarensis* in the Hindu Kush Himalayan (HKH) region under the future climate change scenarios. Our model also predicted a contraction of suitable habitat range (10.86–16.51 %) for *R. geographicum* in the IHR (part of HKH region).

In the present investigation, the overall MaxEnt model predicted that the suitable area of *R. geographicum* may expand towards higher altitudes of Western Himalayan region, while it may contract towards lower altitude in both Western and Eastern Himalayan regions (Fig. 6). These results can be attributed to a rapid deglaciation in the Western Himalaya, which started much before the global average of degradation and may prevail in future climatic conditions (Shekhar et al. 2017). Both range expansion and contraction peaks were observed in RCP 8.5 of future climate scenarios for the year 2070. Such results are in concordance with studies of lichen in HKH (Devkota et al. 2019), and other parts of the world (Binder and Ellis 2008; Ellis et al. 2007a; Ellis et al. 2009; Ellis 2015; Ellis et al. 2014; Allen and Lendemer 2016; Nascimbene et al. 2016; Rubio-Salcedo et al. 2017; Fačkovcová et al. 2017), which also exhibited both expansion and contraction of potential habitat in response to climate change.

## Conclusion

Conservation of pioneer and vulnerable ecosystems at species level has often failed owing to lack of proper knowledge about target species in terms of their habitat stabilities. The application of ENM to extract the basic inventory data of species, i.e., only presence records, to provide prediction of species distribution under changing climate at regional and global scale, may be further used to make recommendations for policymakers and conservationists dealing with impact of climate change and its ecosystem functioning (Sanchez et al. 2011). In lichens, species distribution modeling with MaxEnt extended in to a new tools and it would be especially useful in reconstructing their distribution and potential migratory routes. In the present investigation, we used the maximum entropy–based modeling algorithms, as implemented in ENM software MaxEnt (Phillips et al. 2006), to characterize the environmental niche of the *R. geographicum* and to predict the changes in distribution under climate change scenarios. So far, MaxEnt has not implemented and linked with in any lichenometry-based crustose lichen species to predict the changes in alpine ecosystem. MaxEnt accounts some consequences; for example, it does not estimate directly the probability of occurrence, and rather, it estimates the environmental suitability for the species and can be mapped in a geographical space (Royle et al. 2012). Despite the limitations, it is most and widely used algorithms with good predictive power capabilities. It may be pointed out that actual distribution of any climate sensitive species at regional scale depends upon its variability in physiological tolerance; thus, trait coupled niche modeling analysis is required for its effective conservation. In addition, a long-term species-specific investigation is required at representative sites to develop mitigation measures under the changing climate. Since Nepal constitutes a significant part of the species distributional range, collaborative efforts would go a long way in conserving these critical ecosystems. Trans-boundary cooperation among the Himalayan countries is of critical importance in addressing conservation issues of the Himalayan region.

**Abbreviations** AUC, area under the curve; CCAFS, CGIAR Research Program on Climate Change, Agriculture and Food Security; CMIP5, Coupled Model Intercomparison Project Phase 5; ENM, ecological niche modeling; GCM, global climate model; GHG, greenhouse gases; IHR, Indian Himalayan Region; IPCC, Intergovernmental Panel on Climate Change; MaxEnt, maximum entropy; MRI-CGCM3, Meteorological Research Institute Coupled Global Climate ModelVersion-3; RCP, representative concentration pathway; ROC, receiver operating characteristic curve

**Supplementary Information** The online version contains supplementary material available at https://doi.org/10.1007/s11356-021-15624-5.

**Acknowledgements** This study is part of projects entitled "Timberline and Altitudinal Gradient Ecology of Himalayas, and Human Use Sustenance in a Warming Climate" under National Mission on Himalayan Studies (NMHS) Program (Grant# NMHS/2015-16/LG03/03), and an Institute In-House Project#4 entitled "Mainstreaming Himalayan Biodiversity for Sustainable Development" funded by Ministry of Environment Forest & Climate Change (MoEF&CC), New Delhi, India. The authors are grateful to the Directors, G.B. Pant National Institute of Himalayan Environment (NIHE), Almora, Uttarakhand, and CSIR-National Botanical Research Institute (NBRI), Lucknow, U.P., India, for their encouragement and supports.

**Authors contributions** DK and AP collected field data. DK, RB, and DKU compiled data from Herbarium. DKU, SPS, DK, and RB designed the MS. DK, SPS, AP, SR, and MJ wrote the first draft of the manuscript, and all authors contributed to subsequent revisions. The authors read and approved the final manuscript.

**Data availability** The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Ethics approval and consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Competing interests** The authors declare that they have no competing interests.

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