Predicting the future of species assemblages under climate and land use land cover changes in Himalaya: A geospatial modelling approach

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A B S T R A C T

Community ecology is driven by the patterns and drivers of species assemblages. Montane communities, in particular, are extremely vulnerable to climate change and are one of the first ecosystems to experience climate-induced biological responses. Loss of natural areas driven by human alteration of land use in montane areas may further alter the reorganization of regional assemblages. Several studies have shown latitudinal shifts in individual species as a result of climate change in the twenty-first century, however, the effects of these shifts on assemblages are yet unknown. Therefore, in the current study, we aim to examine the impacts of projected climate and Land Use Land Cover (LULC) changes on dominant species assemblages in western Himalaya. We investigated the spatio-temporal variations in species distribution and composition within the assemblages under climate and LULC changes in two sub-regions- temperate and alpine using ensemble bioclimatic envelope modelling and logistic regression models. While the climate change impacts were found to be more profound in the alpine region, the footprints of LULCC are more significant in temperate areas. The key findings of the study reveal- 1) Number of associated species within assemblages may reduce under climate change (CC) as an outcome of the declining extent of species bioclimatic envelopes; 2) climate change-induced emergence of novel assemblages especially in the alpine region, and 3) significant unfavourable impacts on species assemblages in the temperate region owing to the intersection of climate and LULC changes.

Location
Western Himalayan region, India
Time period
1975 – 2015; projected year- 2070
Major Taxa
Vascular plants

1. Introduction

The hypothesis that climate change is causing altitudinal shifts in species distribution is now well acknowledged and it is anticipated to modify community composition in many terrestrial ecosystems [5,20,40,42]. These claims are based on the latitudinal patterns of growth rate estimated from the field [8] as well as using dynamic global vegetation models [50]. Although the latest research emphasizes species range shifts along altitudinal gradients, using ground-based observations [41,55] and species distribution models (SDM's; [6,21]) modifications in species assemblages as a result of these shifts may have appalling consequences. The species composition of communities and assemblages is, in general, temporally and geographically dynamic. These changes may occur as a manifestation of disturbance events (natural and anthropogenic), or due to stochasticity in assemblages. While climate

change plays a significant role in changing communities, the direct effect of human activity, particularly habitat loss, has been the primary source of biodiversity decline in the twentieth century (Sala et al. 2000) and the combined impact of land use and the future climatic regimes on species assemblages is yet under-explored.

The Himalayas ecosystems are particularly sensitive to the impacts of climate change due to high mountain morphology, microclimatic zones and higher than global average warming in the mountains [36]. Himalayan ecosystems are changing fast under the increasing pressures from land-use change and regional climate change having a direct influence on the structure and functioning of ecological communities [31,38,51]. Global warming in northwest Himalaya is at least 0.7 °C higher than the global average of 1.5 °C accelerating the actual rate of species turnover which may surpass the perceived rates in the region [30]. Typically co-occurrences (assemblages) are studied as the combinations of diverse species sharing a fundamental niche and are consis-

tent across habitats [49]. The loss of key species as a result of assemblage rearrangement can cause considerable changes in community functioning [62]. An understanding of how these alterations in climatic niche limits will rearrange species assemblages through time under the aggregated influence of climate change and land-use trends is critical. It can be expected that we can identify the proxy or representative species if there are high levels of resemblance in the spatial distribution of species richness or species turnover across different taxonomic groups.

The current study projects the temporal dynamics of responses of dominant western Himalayan forest types for important community patterns such as species richness and diversity under the projected climatic and LULCC regimes. We used the intergovernmental panel on climate change assessment report 5 (IPCC AR5) climate scenarios, ensemble bioclimatic envelop (EBE) and LULC modelling approaches to quantify the changes in - (i) number and (ii) types of species in assemblage's prevalent in western Himalaya under CC scenarios as well as CC (2070) + LULCC (2055) scenarios. The detailed study methods are illustrated in Section 3. Using multiple methods to analyse changes in assembly patterns over spatiotemporal domains offers an opportunity to separate possible mechanisms of explanation. Although the study focused on the structure of species assemblages rather than species interactions directly, the results, in general, reflect the probable scenarios of species assemblages in the western Himalaya under the CC and LULCC scenarios.

2. Study area

Western Himalayas forms the westernmost section of the vast Himalayas mountain range comprising two states Himachal Pradesh and Uttarakhand (Fig.1). Forests account for about twenty-five per cent of the total geographic area of this zone. The region receives an average rainfall of about 100 cm in the form of both rainfall and snow with winter temperatures generally remaining below 5 °C. It has the presence of some of the world's richest temperate montane plant communities. The forest vegetation types in the study region are classified chiefly into eleven formations that range from Submontane broadleaf ombrophilous forests (below 1000 m) to very high-montane scrub (above 3500 m and up to 4900 m).

Currently, the forests of this ecoregion are threatened by recent climate change, conversion of land to agriculture, increasing logging, and fuel collection. With the proliferation of horticulture occupying a prime position in the land-use system most of the areas can now be defined as Horti-agri-pastoral (http://www.fao.org/docrep/x5672e/x5672e02.htm). Also, people from around the world flock here as pilgrims or tourists. Their presence has spurred ill-planned roads, trails, and hotels in the region.

3. Methods

3.1. Species data

Six major forest vegetation types representing a wide variety of different taxa, dominance, endemicity and current threat status were selected for the study (Table 1). The "presence only" species occurrence database was pooled from biodiversity characterization at landscape-level project data [47] at https://bis.iirs.gov.in/, field trips, herbaria and online portals like GBIF (Global Biodiversity Information Facility) available at http://www.gbif.org/ [19]. The species database was checked for duplicate records and sampling bias. It was ensured that only one species location was used per 1 km^2 to maintain uniformity in species location points. The credibility of species occurrence data acquired from herbaria was validated with 90 m SRTM DEM data for topographic information.

3.2. Climate data

The specifications of the climate layers used in the study are mentioned in Table 1. Worldclim data was used for the study of high spatial resolution (~ 1 km^2) suitable for the montane region [26]. The data has been widely used in building species distribution models [7]. It provides 19 derived bioclimatic variables which describe annual tendencies, seasonality and extreme climatic conditions related to temperature and precipitation aggregated across a target temporal range of 1970–2000 and 1960–1990. The future climate projections include downscaled global climate model (GCM) data from the coupled model inter-comparison project (CMIP5) based on the IPCC AR5 scenarios. These scenarios are based on representative concentration pathways (RCPs) i.e., the total radiative forcing by 2100.

For the study, we used the RCP 4.5 (Wise et al., 2009) which is a more moderate emissions scenario and RCP 8.5 [44] which is a high emissions scenario based on "business-as-usual" for the year 2070. To reduce the anomalies in the climate data, we used an ensemble of GCM combinations to project future climate Lutz et al., n.d. [33]. The projected climate data from three primary models contributing to the AR5: GCMs- GFDL-CM3 [23], MRI CGCM3 [64] and CNRM CM5 [61] were averaged and used for developing EBEs. For the topographic data, SRTM digital elevation model data (DEM; ~90 m) was used. An aspect map was generated from DEM data with the help of surface features in Arc GIS (version −10.3.1) for further analysis.

3.3. LULC data

Decadal LULC maps for - 1975, 1985, 1995, 2005 and 2015 were prepared using visual interpretation of two seasons (pre-monsoon & post-monsoon) satellite data at 1:250,000. A set of Landsat Multispectral Scanner (MSS) and Landsat Thematic mapper (TM)/ Linear Imaging Self-Scanning (LISS-1) data were used to modify LULC maps of 1985 and 1995 respectively (P. S. [48]). LULC map of 1975 was prepared using Landsat MSS data. The satellite images were downloaded from the USGS-earth explorer available at https://earthexplorer.usgs.gov/. For more recent years 2005 and 2015, Advanced Wide Field Sensor (AWiFS) and LISS-III data was used (Table 2). AWiFS data aboard IRS-P6 (~56 m) has been used to successfully generate the LULC information in various studies [27]. The data was acquired from the Indian geo platform of ISRO at https://bhuvan-app3.nrsc.gov.in/data/download/index.php. The LULC maps prepared for above mentioned years were classified into ten broad classes- evergreen forest, deciduous forest, snow/ice, barren land, deciduous forest, scrubland, grassland, water bodies, plantation and built-up (Anderson, 1976).Table 2

3.4. Modelling species bioclimatic envelops

Ten different algorithms were used to develop EBEs for each species using climate and topographic data. We used the BIOMOD2 package [56] in R software (version- 3.2.0; R Development Core Team, 2011) that offers a platform for ensemble forecasting of species distributions addressing methodological ambiguity related to different modelling approaches and the exploration of species-environment relationships. These algorithms include Generalized Linear Models (GLM; [34]), Generalized Additive Models (GAM; [25]), Generalised Boosted Models (GBM; [45]), Classification and Regression Tree analysis (CART; [9]), Artificial Neural Networks (ANN; [46]), Surface Range Envelope (SRE; [11]), Flexible Discriminant Analysis (FDA; [24]), Multiple Adaptive Regression Splines (MARS; [22]), Random Forest (RF; Leo [10]) and Maxent [4]. The inclusion of bioclimatic layers was based on the importance value of predictors (Fig 3) and Pearson's correlation analysis in R to avert multicollinearity amongst the variables for each species ([17]; Fig. A1). Models performance was tested using receiver operating characteristic (ROC) and True Skill Statistic (TSS) scores which are frequently used to evaluate species distribution models performance [32].
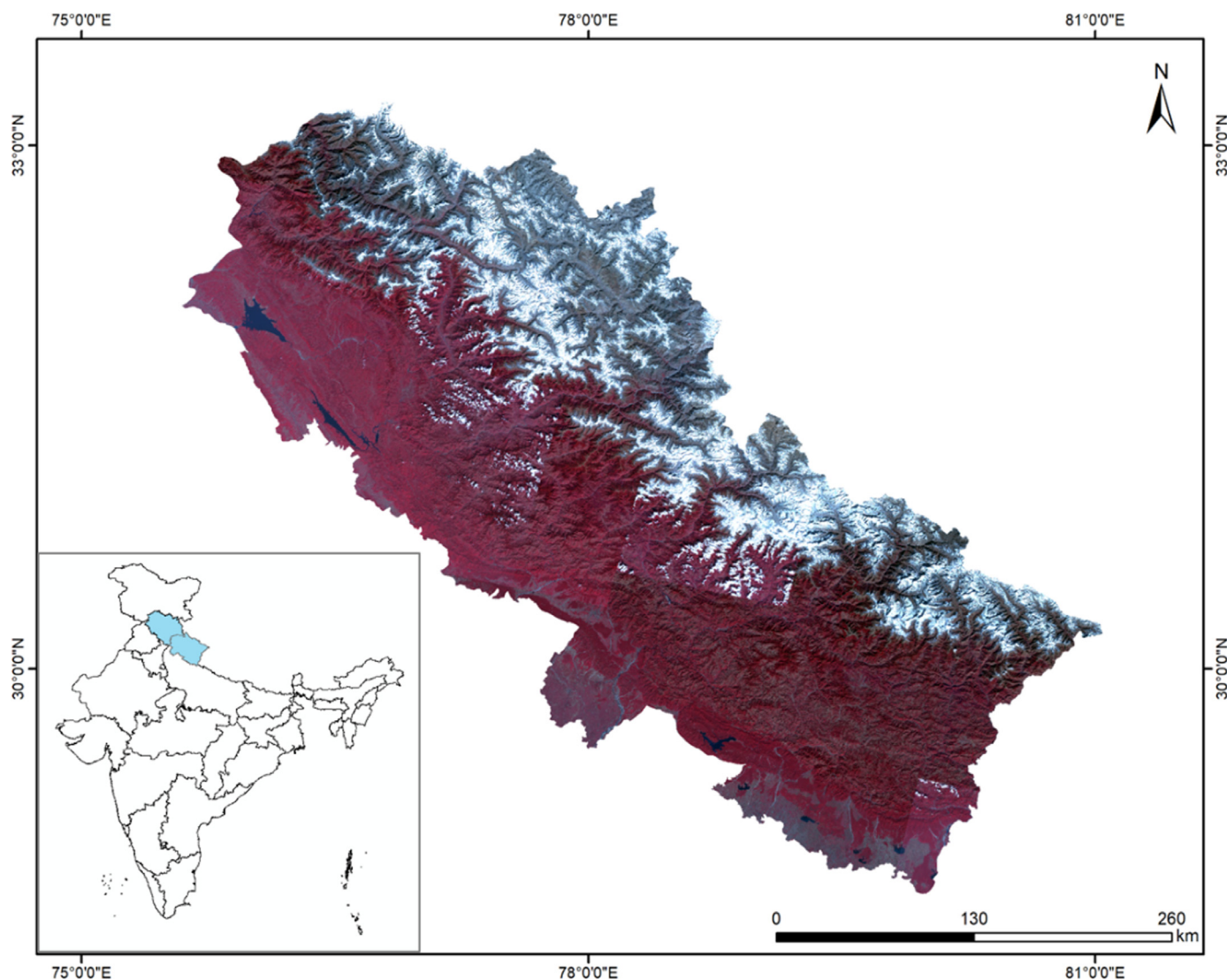
Fig. 1. Figure 1 Location and false color composite image of the study area (Data: AWiFS 2015).

ROC is plotted between sensitivity and (1- specificity) across all possible thresholds between 0 and 1. Where sensitivity is the measure of the proportion of instances of presence correctly predicted as presence, specificity is the proportion of instances of absence correctly predicted as an absence. If the curve is above the diagonal of no discrimination, i.e. AUC > 0.5, a model is said to discriminate better than chance. TSS scores range from −1 to 1, where +1 indicates a perfect ability to distinguish suitable from unsuitable habitat, while values of zero or less indicate a performance no better than random [1]. Models performing (TSS > 0.4 and ROC > 0.8) were included in the ensemble model (Fig. A2). EBEs as a proxy of species distribution ranges were produced for each species for three scenarios - current, RCP 4.5 and RCP 8.5. The detailed methodology is presented in Fig 2.

3.5. LULC modelling

The process of LULC modelling can be described in three major steps- 1) change analysis, 2) transition potential modelling and 3) LULCC prediction [35]. We performed change analysis between the years 1975 and 2015 using the respective LULC maps in Idrisi Land Change modeller (LCM). The change analysis provides an assessment of quantitative change by estimating the gains and losses between different land cover types, the net change in a land class and the transition of land cover in-formation. Change analysis was followed by transition potential where it maps the area of change and evaluate the relationship between frequency of change and explanatory variables using evidence likelihood. LCM groups changes in LULC with similar driving variables into sub-models. Nine driver variables- annual precipitation, mean annual temperature, elevation, slope, soil type, distance from roads, distance from disturbances, distance from urban and population density based on familiarity with the study area were identified for LULC modelling. Normalization of these driver variables was performed before introducing them in the model. Logistic regression available in land change modeller in Idrisi platform was used to model and analyse changes in different land classes from 1975 to 2015 and anticipate their likelihood of change by 2055 in western Himalaya.

3.6. Species assemblages in western Himalaya

Species assemblages under baseline and CC and LULCC scenarios were analysed using the species distribution results obtained from EBE modelling. Species assemblages in different communities comprising of *A. pindrow, B. utilis, C. deodara, P. smithiana, P. wallichiana, Q. floribunda, Q. semecarpifolia, Q. leucotrichophora, R. arboreum, T. wallichiana, J. indica, J. communis, D. hatagirea* and *L. obovata* were evaluated based on species no. and structure.

Table 1
Details of the species used (Source: The IUCN Red List of Threatened Species 2012; Rana and Samant, 2009).

| S.No	Species	Vegetation type	Current population status	Current Threats
1.	*Abies pindrow* (West Himalayan Fir)	Temperate mixed coniferous forest	Stable	Species is logged for its timber
2.	*Betula utilis* (Himalayan birch)	Subalpine forest	Decreasing	Over-exploitation due to its high medicinal value.
3.	*Cedrus deodara*(Deodar Cedar, Himalayan Cedar)	Temperate mixed coniferous forest	Unknown	Deforestation and conversion of forests for agriculture
4.	*Picea smithiana* (Indian Spruce, Morinda Spruce,)	Temperate mixed coniferous forest	Decreasing	Logging without adequate natural regeneration
5.	*Pinus wallichiana* (Blue Pine, Himalayan Pine)	Temperate mixed coniferous forest	Stable	over-exploitation
6.	*Quercus floribunda* (Moru Oak)	Moru Oak forest	Decreasing	Deforestation, Pine invasion, Overexploitation
7.	*Quercus semecarpifolia* (Kharsu Oak)	Kharsu Oak forest	Decreasing	Deforestation, Pine invasion, Overexploitation
8.	*Quercus leucotrichophora* (Banj Oak)	Banj Oak forest	Decreasing	Deforestation and conversion of forests for agriculture along with pine invasion pose local threats
9.	*Rhododendron arboreum* (Buransh)	Oak- Fir forest	Unknown	Deforestation and overexploitation due to various socio-economic utilities
10.	*Taxus wallichiana* (Himalayan Yew)	Temperate mixed coniferous forest	Endangered	Extremely exploited for its application in anti-cancer drug paclitaxel or similar chemicals. As much as 90% decline been reported in India
11.	*Juniperus indica* (Black Juniper, Wallich's Juniper)	Dry temperate mixed forest	Decreasing	Exploited for incense and firewood. Fragmentation and overgrazing also poses threats.
12.	*Juniperus communis* (Common Juniper, Mountain Juniper)	Dry temperate mixed forest	Decreasing	Habitat degradation
13.	*Dactylorhiza hatagirea*'Salam Panja' or 'Hatta Haddi'	Temperate, Alpine	Endangered	Lack of management and conservation plan. Overexploited for its medicinal properties.
14.	*Lonicera obovata*(Blueberry Honeysuckle)	Moist alpine scrub	Threatened	Overexploitation due to medicinal properties.
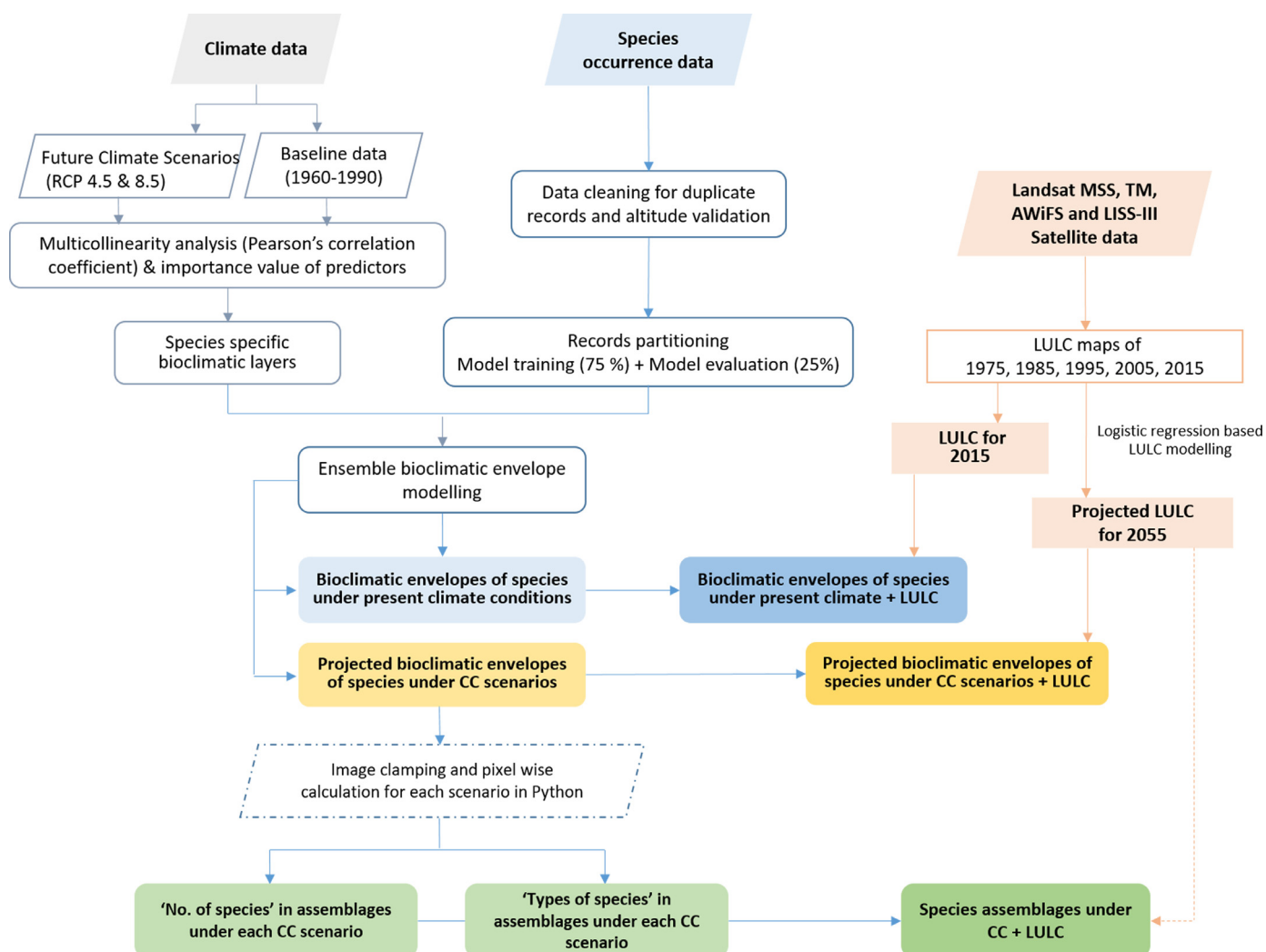
Fig. 2. Flowchart of the approach used in the study.

Table 2
Details of the satellite data used.

S.No	Satellite/sensor	Spatial resolution (m)	Acquisition year
1.	Landsat MSS	60	1975
2.	Landsat MSS	60	1985
3.	Landsat TM and LISS-1	30, 72	1995
4.	LISS III	23.5	2005, 2015
5.	AWiFS	56	2015

3.6.1. Number of associated species

The species distribution results obtained as raster images from EBE modelling for each species under baseline and CC scenarios were re-classified into binary maps i.e. suitable and non-suitable areas using a threshold probability in Arc GIS. The threshold for probability of presence was determined at the intersection of true positive rate (TPR) and true negative rate (TNR) for each species [12]. These reclassified images were clamped, and a pixel-wise raster image of the number of species was created using codes in Python software (version- 3.6.2). The approach was repeated for each CC scenario as well as CC + LULCC scenarios. These raster images were evaluated in Arc GIS and R software.

3.6.2. Types of species assemblage

The probability distribution in raster images obtained from EBE modelling was reclassified for each species using threshold probability. The classes below the threshold probability were dropped, and the remaining classes were retained for final analysis. We associated higher probability classes with higher dominance. The output layers (raster images) were clubbed together and the eco-existing species were analysed in python [59]. Following this, the subclasses of different species assemblage types in the output map were recorded in the corresponding vegetation type based on Champions and Seth forest classification (Champion & Seth, 1968). For the climate change scenarios, the classes for new species assemblage types were retained as the same. The process was repeated for each CC and CC + LULCC.

4. Results

4.1. Predictor variables

A major application of EBE is to find out which variables are the most important for a species' distribution. In our study, the importance of precipitation and temperature for different species distributions varied with each species (Fig 3). The variables with the highest importance in defining species ranges were temperature seasonality (BIO4) and temperature annual range (BIO7; Fig 3).

Dry alpine scrub viz. junipers were found to be most responsive to changes in mean temperature of coldest quarter (BIO11) and precipitation of coldest quarter (BIO19). For the moist alpine scrub, mean temperature of warmest quarter (BIO10), temperature annual range (BIO7) and precipitation parameters such as annual precipitation (BIO12), precipitation of- coldest quarter (BIO19), wettest month (BIO13) were identified as most important variables. Annual precipitation (BIO12), tem-

perature annual range (BIO7) and mean temperature of coldest quarter (BIO11) mostly defined the distributions of Oak species (Fig 3).

In addition to temperature annual range (BIO7) and temperature seasonality (BIO4), precipitation of coldest quarter (BIO19) and annual mean temperature (BIO1) demonstrated the most variance in the climatic niche of temperate conifer species viz. *C. deodara* and *P. wallichiana*. For *T. wallichiana*, besides BIO7 and BIO1, precipitation of the driest quarter (BIO 17) has a robust influence on its distribution. Similarly, the distribution of *R. arboreum* is strongly related to temperature annual range (BIO7) and temperature seasonality (BIO4) Fig. 3.

4.2. Climate and land-use changes prompted modifications in Himalayan species richness

Currently, the number of species in assemblages increase with elevation and then reduces at higher altitudes having species-rich areas in the central and south-eastern parts (Fig 4). Although the no. of species in species assemblages remain unaffected due to the current LULC setting, it has significant impacts on the cumulative *area* of current species assemblages in the study area (Fig 4). Ongoing land-use changes have noticeably encroached upon the suitable climatic niche of species assemblages *especially* with 03 - 06 species (Figs. 4 and 5).

As the climate changes, the maximum no. of species in a community may decline from eleven to six in the study region (Fig 4). Communities having 04 to 06 species in assemblages may face a higher probability of range losses in RCP 8.5 where the probability of loss of suitable climatic niche of species at lower altitude areas is severe. This trend is more apparent in the mid-elevation Himalayan region occupied by temperate mixed coniferous forests. However, under RCP 8.5, smaller sized communities (having 03 to 04 species) are projected to spread as a result of an upward shift in species bioclimatic envelopes. The projected LULC dynamics is also anticipated to cause further shrink in total areas of species assemblage (Fig 6). In general, it can be inferred that impacts of the projected CC and LULCC are stronger on the communities having a higher no. of species assemblages.(Fig. 6).

4.3. Future projections in Himalayan species assemblages

EBE modelling results were used to evaluate the probability of types of species assemblages that can be found as co-existing species in a particular vegetation type for both – baseline and future scenarios of climate (2070) and land-use change (2055). Results suggest that the dominance of temperate mixed coniferous forests in terms of range areas may be compromised due to CC and LULCC (Fig 7). It is also expected that the area associated with species of oak, dry alpine shrubs and cedar will also decrease. In contrast, moist alpine scrub, rhododendron and blue pine forests show a notable expansion in CC scenarios (Fig 7). An important observation is an emergence of probable seventeen and nine novel species assemblages in RCP 4.5 and RCP 8.5 respectively (Tables 3–4). It is observed that these new associations are mainly limited to alpine vegetation, where current climatic conditions may open up new areas to support the upward movement of subalpine/treeline species. When considering the impacts of climate change scenarios alone, it can

Table 3
Projected new species assemblages under RCP 4.5.

| Code	Vegetation type	Code	Vegetation type
1	*L. obovata + R. arboreum*	10	*B. utilis + J. communis + R. arboreum*
2	*J. communis+R .arboreum*	11	*J. communis+L. obovata*
3	*B. utilis+R. arboreum*	12	*J. indica+L. obovata+R. arboreum*
4	*B. utilis+L. obovata+R. arboreum*	13	*J. communis+J. indica+L. obovata + R. arboreum*
5	*J. indica+R. arboreum*	14	*L. obovata+P. smithiana + R. arboreum*
6	*Temperate Mixed Coniferous Forest + R. arboreum*	15	*L. obovata+P. wallichiana + R. arboreum*
7	*B.utilis+J.communis+L.obovata + R. arboreum*	16	*B. utilis+J. communis+L. obovata + R. arboreum*
8	*J. communis+L. obovata + R .arboreum*	17	*B. utilis+J. communis+L. obovata*
9	*J. indica+L. obovata*		
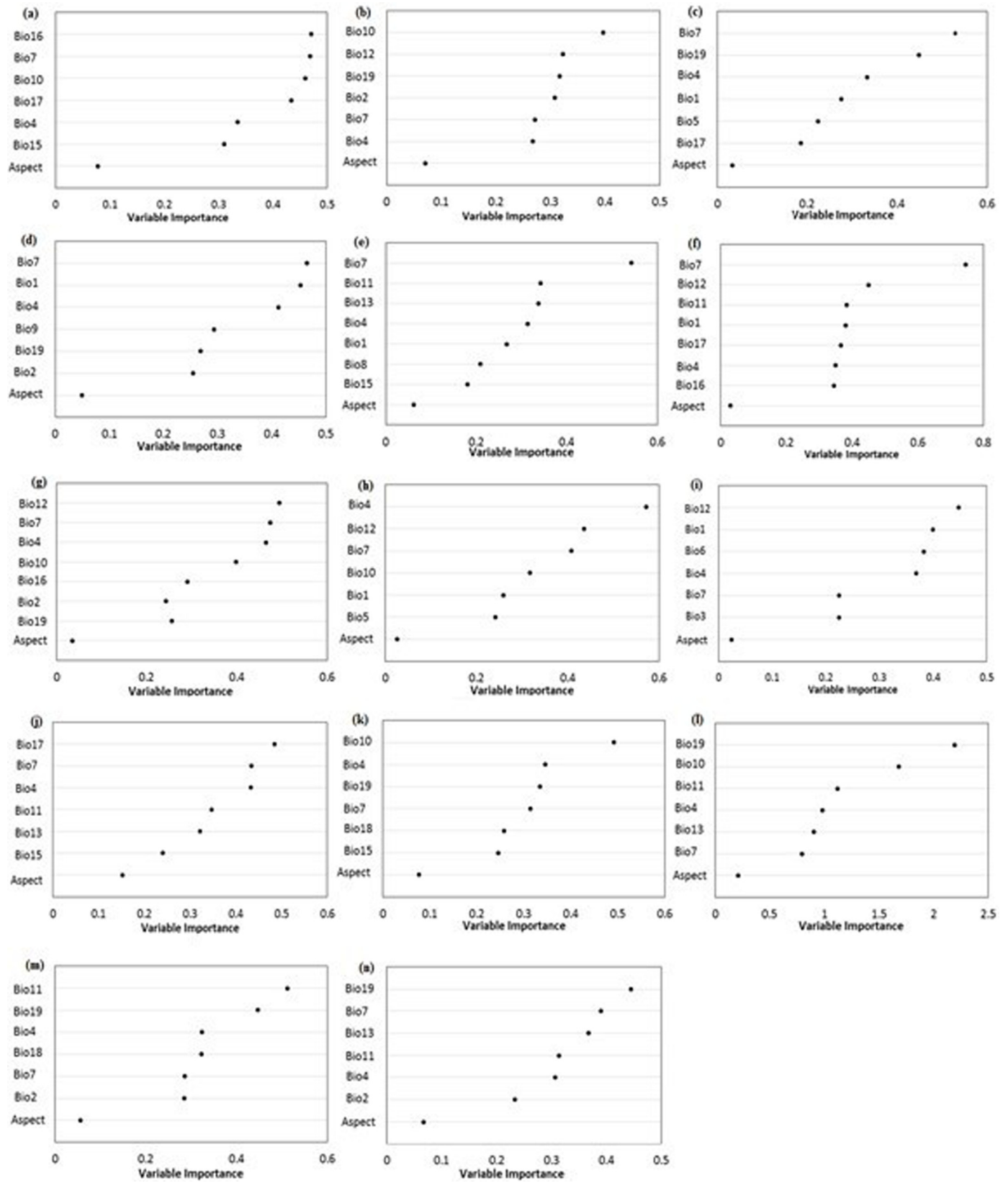
Fig. 3. Variable importance value of predictor variables for (a) A. pindrow, (b) B. utilis, (c) C.deodara, (d) P. wallichiana,(e) Q. leucotricophora, (f) Q. floribunda, (g) Q. semecarpifolia, (h) R. arboreum, (i) P.smithiana, (j) T. wallichiana, (k) D. hatagirea, (l) J. indica (m) J. communis (n) L. obovata.
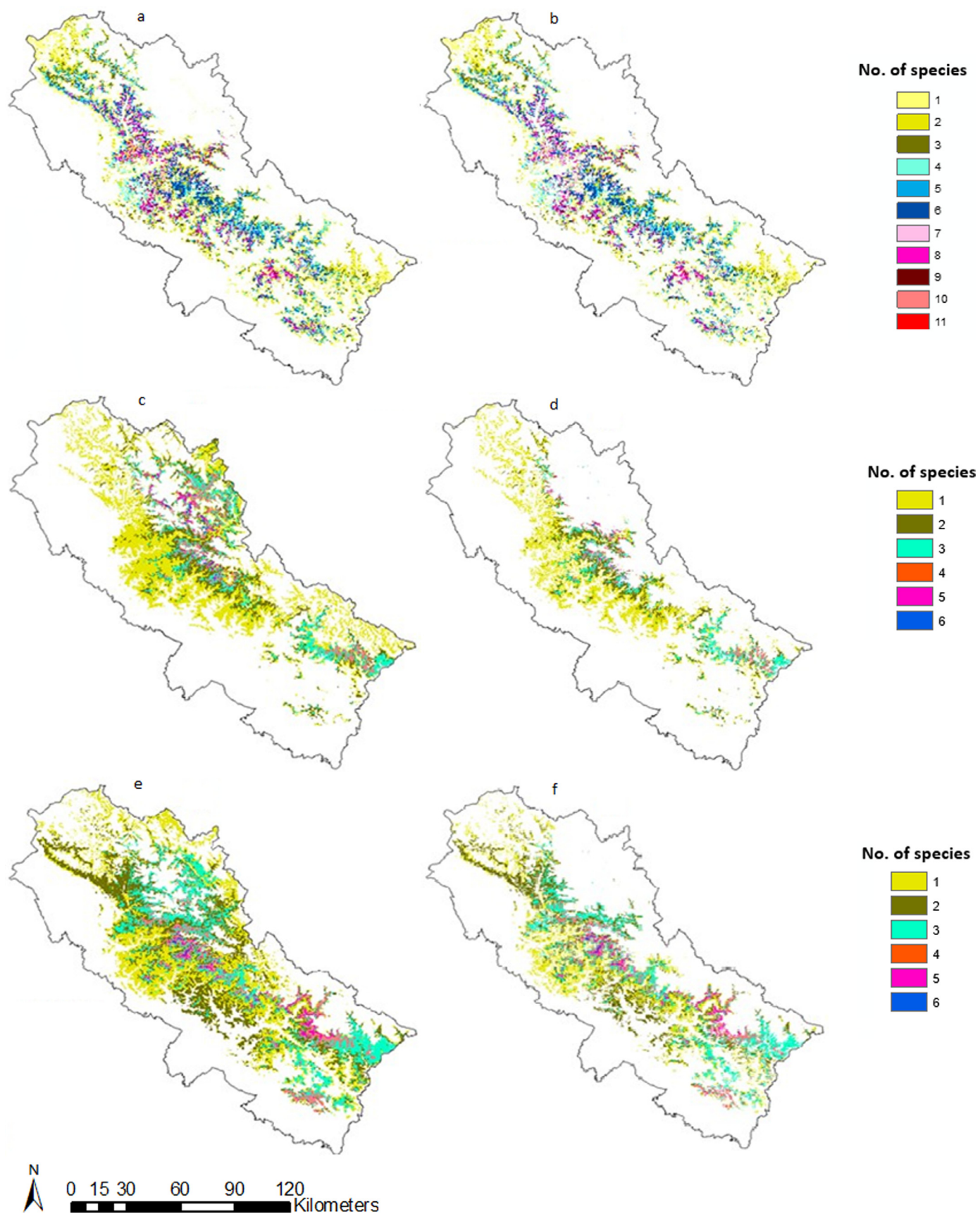
Fig. 4. No. of species in assemblages under (a) baseline: climate scenario only, (b) baseline: climate + LULC; (c) RCP 4.5: climate scenario only, (d) RCP 4.5: climate + LULC, (e) RCP 8.5: climate scenario only, (f) RCP 8.5: climate + LULC.
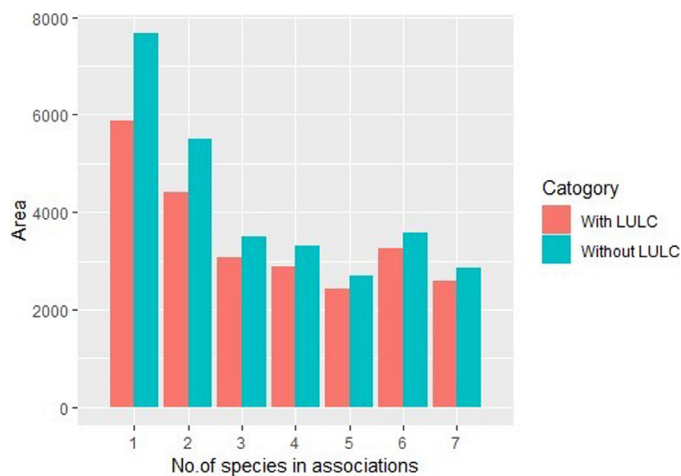
Fig. 5. Area for no. of species (km^2) in assemblages under baseline conditions.

be loosely concluded that the CC impacts effects of climate change scenario are more intense in RCP 4.5 with higher quick turnover in species assemblages as compared to RCP 8.5. The climatic niche of temperate and alpine species are also projected to overlap (Fig. 7), Table 3 and Table 4.

Table 4
Projected new species assemblages under RCP 8.5.

Code	Vegetation type
1	*L. obovata + R. arboreum*
2	*T. wallichiana + R. arboreum*
3	*L. obovata + T. wallichiana + R. arboreum*
4	*C. deodara + P. smithiana + T. wallichiana + R. arboreum*
5	*L. obovata + R. arboreum + T. wallichiana*
6	*C. deodara + Q. semecarpifolia + T. wallichiana + R. arboreum*
7	*C. deodara + A. pindrow + R. arboreum*
8	*L. obovata + C. deodara + T. wallichiana + R. arboreum*
9	*T. wallichiana + L. obovata*

To investigate the effect of LULCC, the changes in ranges of species assemblages were compared between the 'climate change only' and 'climate change + LULC' scenarios. Due to current land use, there is a notable fragmentation of temperate mixed coniferous forest and banj oak (Fig 8). The anticipated area of each species association type under RCP 4.5 has decreased due to the effects of man-made LULC alterations with blue pine, banj oak, wet deodar, and temperate mixed coniferous forest as the most affected vegetation types (Fig 9). A similar trend of loss in the probable areas of species assemblages due to projected LULCC is predicted under the climate change scenario of RCP 8.5. The highest loss is observed in blue pine forests, whereas moist alpine scrub and the new assemblages (1, 4, 5, 6, 8, 9) are expected to be least affected
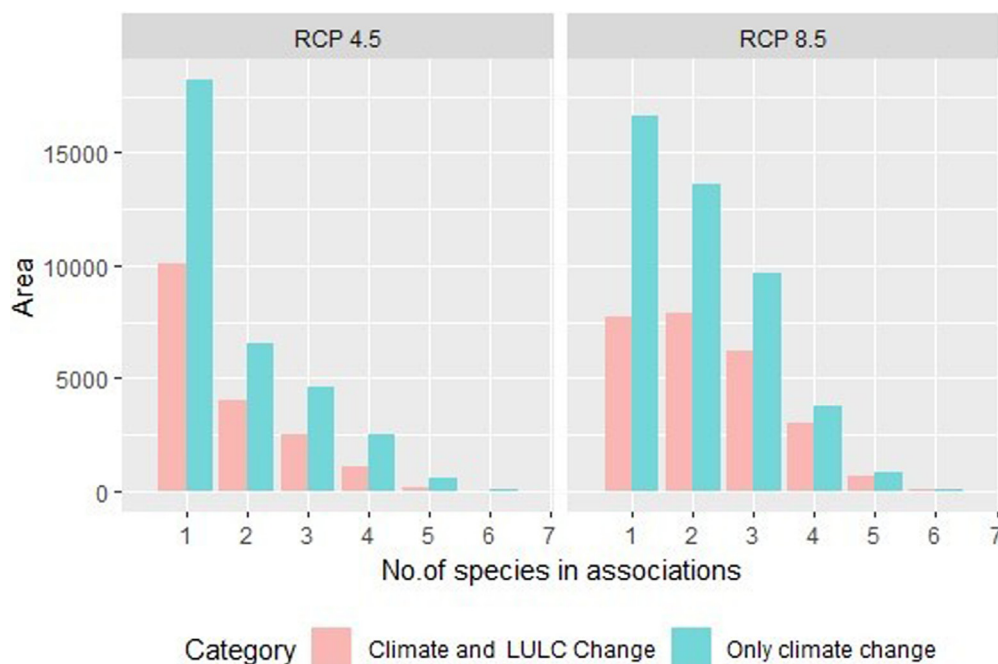

Fig. 6. Area for no. of species (Km^2) in assemblages under projected CC & LULCC scenarios.

Table 5
Projected common areas (in km$^{2)}$) of species assemblages between present and CC scenarios.

| RCP 4.5 Vegetation type	Area	RCP 8.5 Vegetation type	Area
Banj oak	241.47	Banj oak	882.74
Blue pine	3398.37	Blue pine	5732.58
D.hatageria	95.18	D.hatageria	42.31
Deodar+R.arboreum	150.64	Deodar	917.96
Juniperus scrub	62.77	Deodar + R.arboreum	667.15
Moist alpine scrub	400.96	Temperate mixed coniferous forest	5870.22
Moist Deodar forest	1118.99	Moist alpine scrub	233.24
Moru oak	30.63	Moru oak	798.11
R.arboreum	1468.41	R.arboreum	398.16
Temperate mixed coniferous forest	170.09		
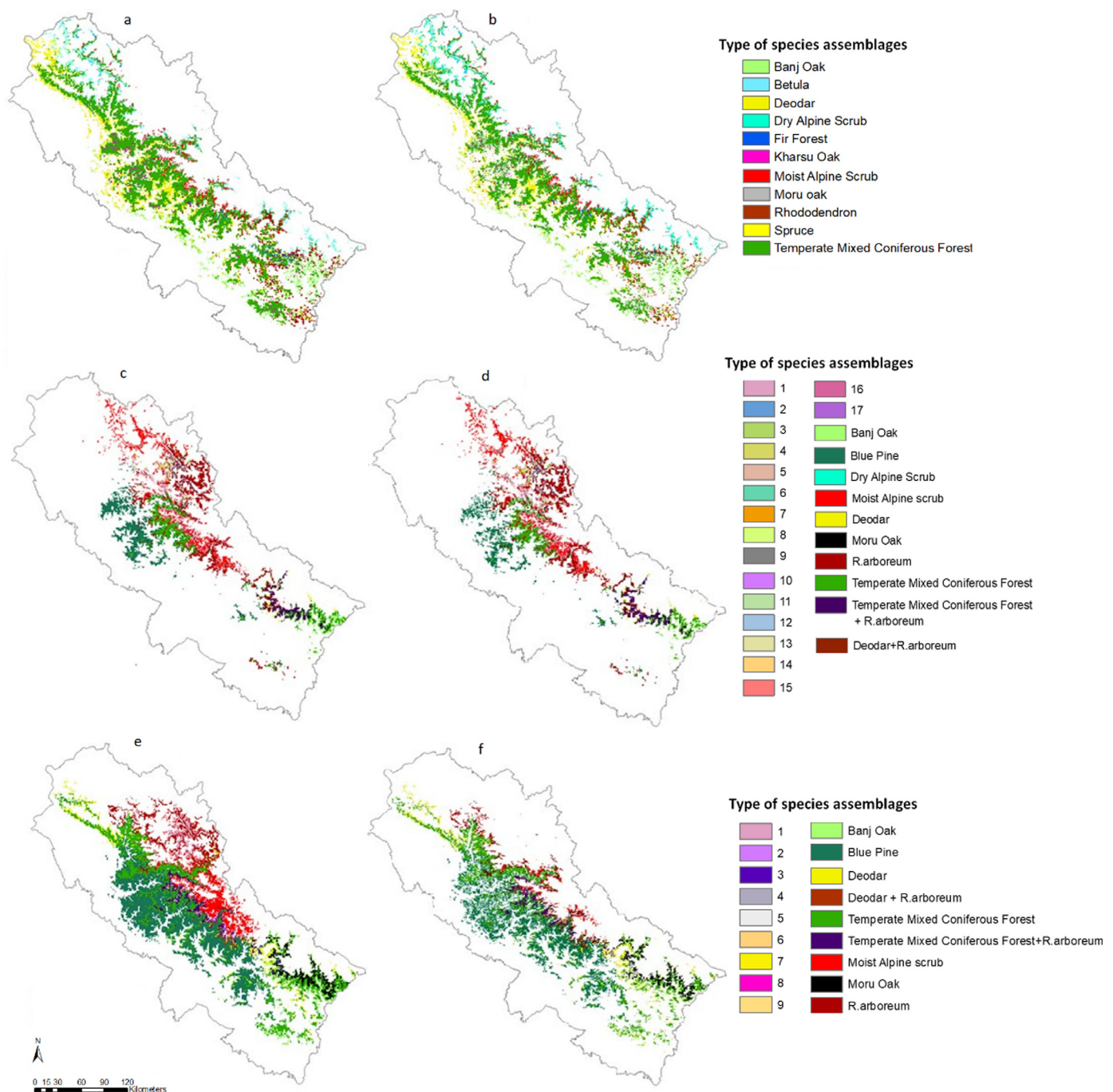
Fig. 7. Species assemblages types under (a) baseline: climate scenario only, (b) baseline: climate + LULC; (c) RCP 4.5: climate scenario only, (d) RCP 4.5: climate + LULC, (e) RCP 8.5: climate scenario only, (f) RCP 8.5: climate + LULC.

by projected LULCC (Figs. 8, 9 and 10). Our findings also highlight the areas of precedence in the study region based on the projected common ranges between the present and CC scenarios. In RCP 4.5 CC, the high priority areas are located in the central and south-eastern region of Himachal Pradesh as well as northern and northeastern parts of Uttarakhand (Fig 11). Under RCP 8.5 CC, these areas are extended to northern (Himachal Pradesh) and central and southeastern (Uttarakhand) parts of the study region (Fig 12). According to these projections, the ranges of forest types such as banj oak, blue pine, deodar+*R. arboreum*, moru oak, and temperate mixed coniferous forest are more vulnerable in RCP 4.5 than in RCP 8.5 (Table 5), Figs. 11 and 12.

5. Discussion

The study looks at the spatio-temporal changes in the size and composition of species assemblages comprising of dominant taxonomic groups of western Himalaya as a result of their potential response to the bioclimatic regime under the combined impact of projected CC (2070) and LULCC (2055). Under climate change scenarios, rapid species turnover is observed in all of the assemblages studied in the study, which can be explained by climate-driven range shifts [60]. Different climate regimes (RCPs) are predicted to affect the composition and structure of species assemblages. While certain vegetation types, such as temperate mixed coniferous forests and dry alpine scrub, are
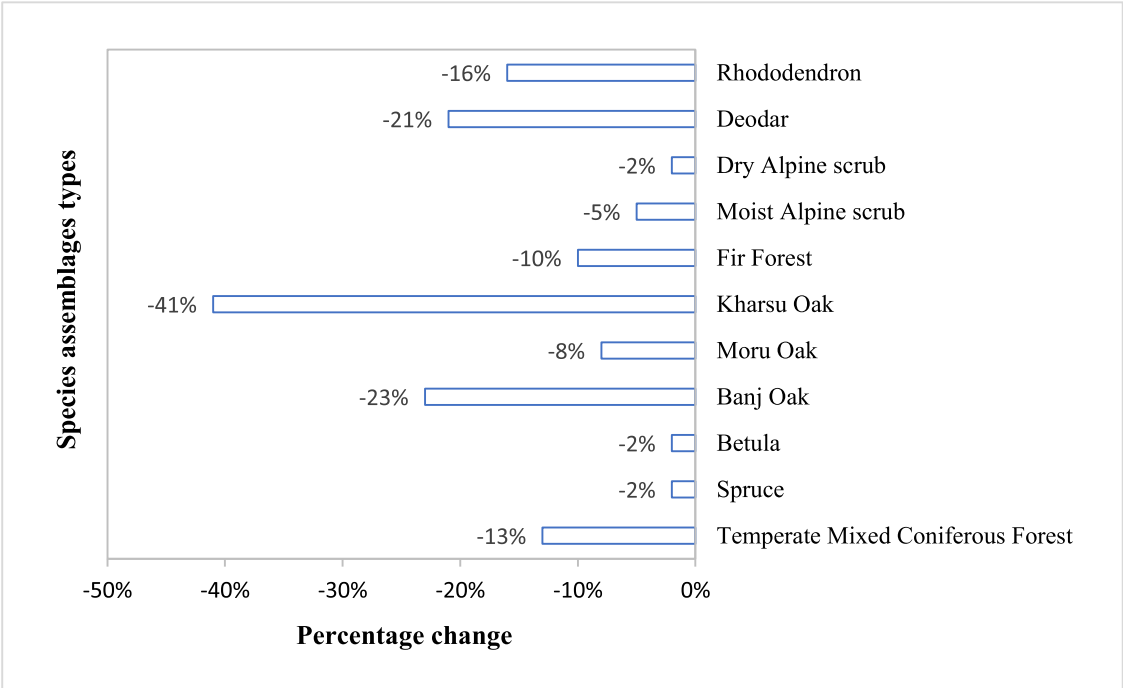
Fig. 8. Percentage change in the area of probable species assemblages due to LULC under baseline (present) conditions.
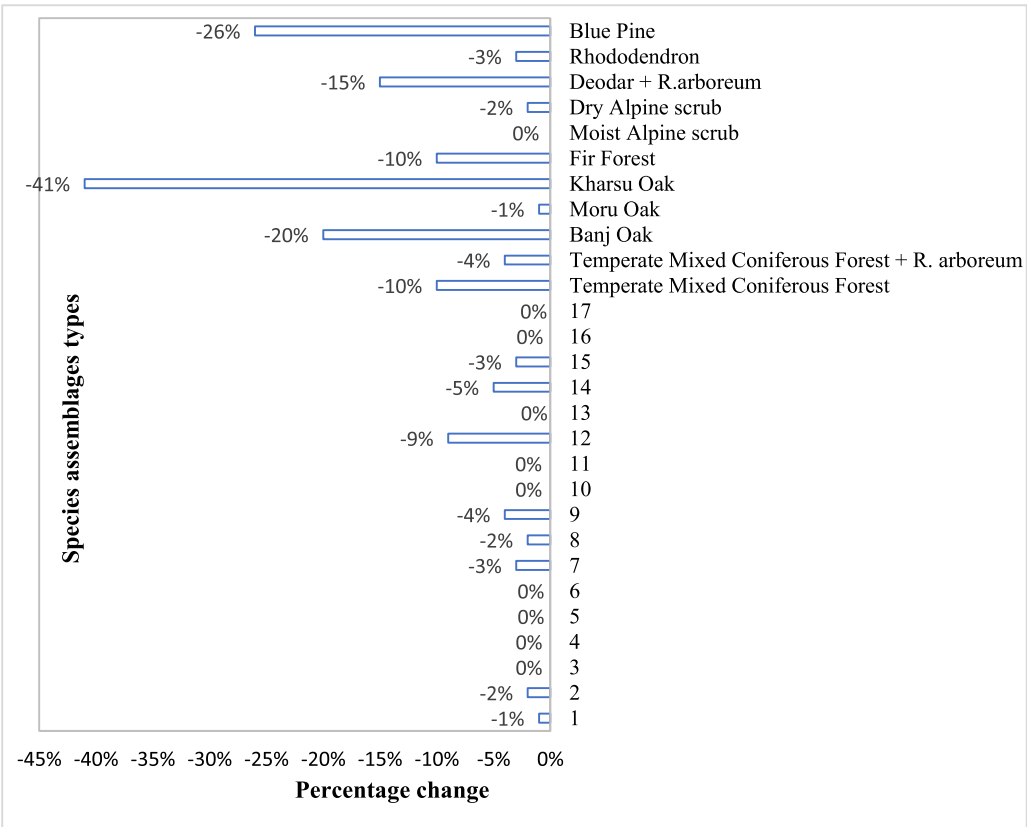

Fig. 9. Percentage change in the projected area of species assemblages due to LULCC under RCP4.5 CC scenario.
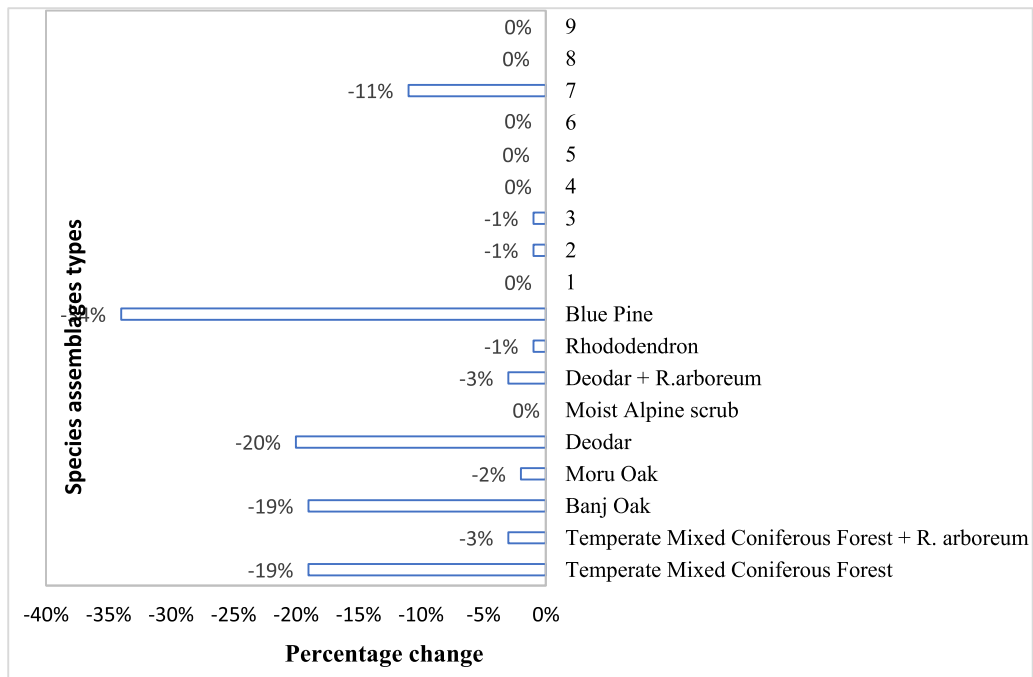
Fig. 10. Percentage change in the projected area of species assemblages due to LULCC under RCP8.5 CC scenario.
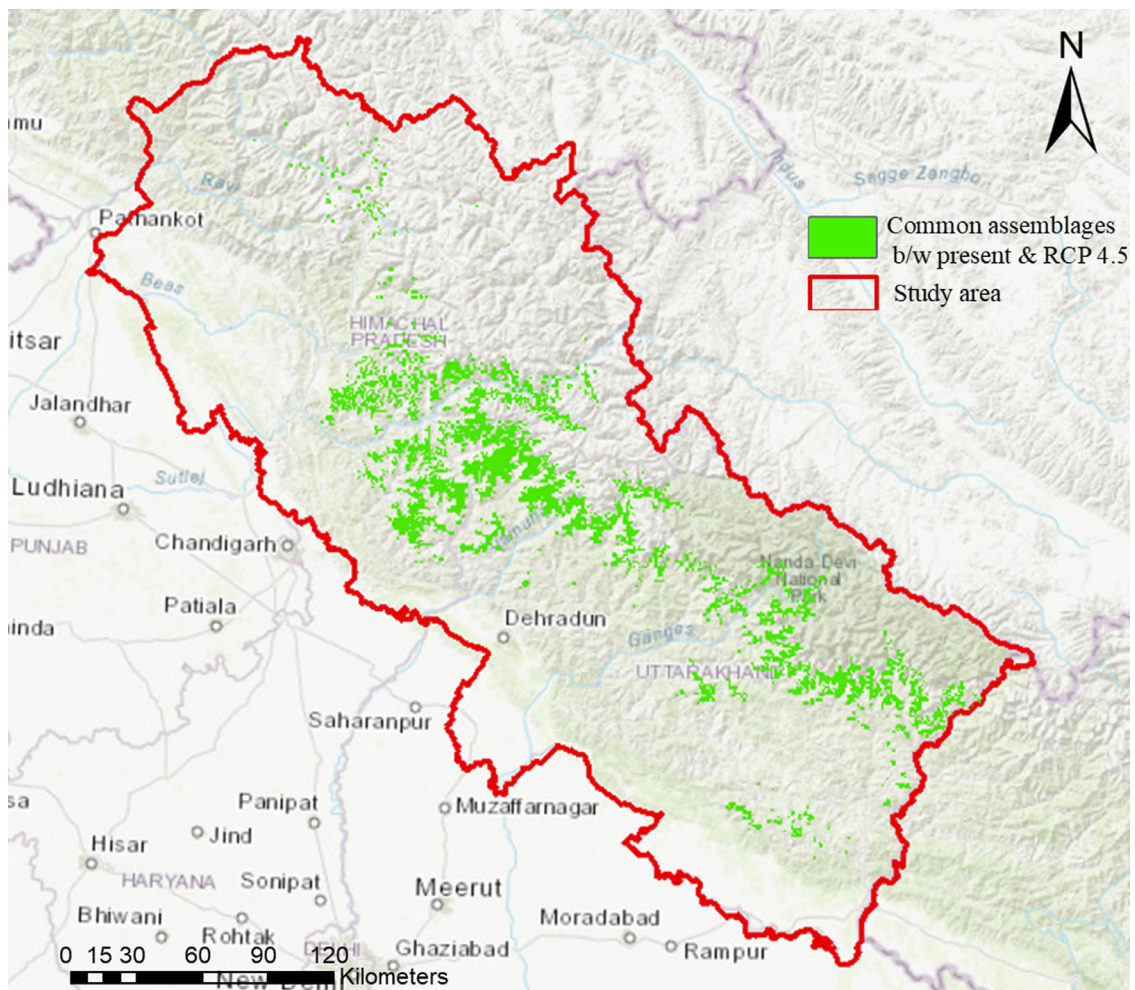

Fig. 11. Common areas of species assemblages between present and RCP 4.5 CC scenario.
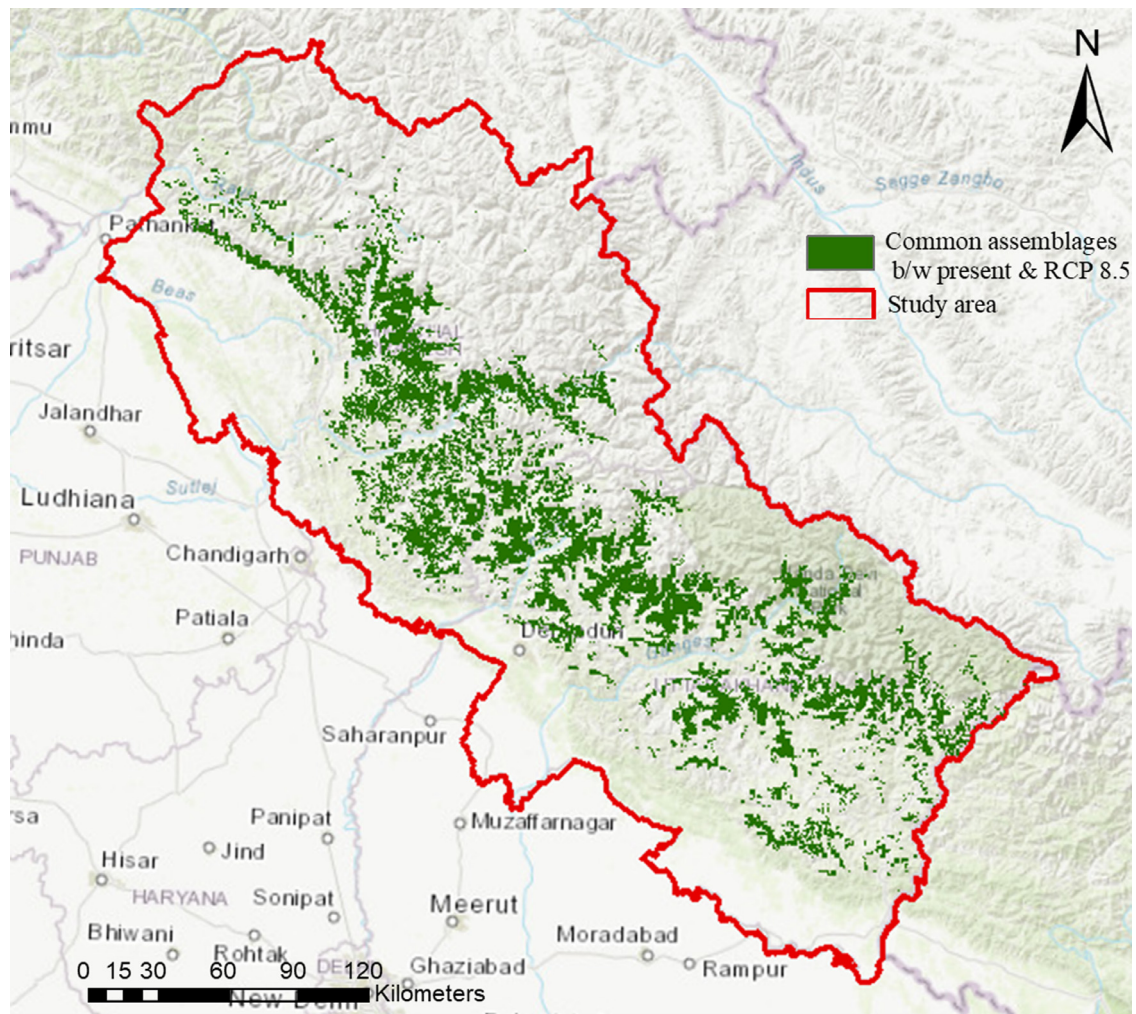
Fig. 12. Common areas of species assemblages between present and RCP 8.5 CC scenario.

likely to lose their current ranges, others, such as blue pine and moist alpine scrub, may see range expansions, according to the findings. However, these projected range expansions may be substantially undermined by LULC changes [54].

As a result of changes in existing climatic conditions, the majority of the region may be pushed out of the investigated species' existing climatic niche. Projected instability in temperature seasonality (BIO4) and elevated mean temperature annual range (BIO7) can be related to a decline in the potential future suitable areas of these vegetation types. Other significant bioclimatic variables, such as annual precipitation (BIO12) and precipitation of the wettest quarter (BIO16), which are thought to have a role in limiting species distributions in the current climate, are diminishing in temperate zones due to climate change. During the hot summer months in western Himalaya, BIO16 represent monsoon rainfall, which accounts for 80% of precipitation and relieves water and heat stress (Zobel & Singh, 1995). A delay in monsoon can impair the regeneration of desiccation-sensitive seed-bearing species such as oaks ([37,53]). The majority of these Himalayan forest species thrive under sufficient rainfall and low-temperature regimes ([52]; Negi, 2000), therefore an irregular precipitation regime, along with rising temperature, may affect these species [16,57]. Due to the steep elevation gradient and considerable microclimate heterogeneity, however, the fluctuation in the forecasted climate is not consistent in the western Himalaya, resulting in varied spatial patterns of species distributions.

Although species are responding to climate change by tracing their climatic niche via shifts in their ranges, ecological assemblages are not.

Our model has projected a significant drop in the area of species assemblages with more than four dominant species. A projected increase in the area of vegetation with fewer than two dominating species points to future forest ecosystems with very little biodiversity [13]. This increase can also be attributed to species colonizing new areas and moving upslope above treeline as captured in our model outputs. While a shift in optimal climate envelopes resulted in a considerable expansion in the range areas of birch, blue pine, and deodar + R. arboreum forests under climate change scenarios, the future of Oak forests, dry alpine forests, and temperate mixed coniferous forests remains bleak [43]. Under warmer conditions, the ranges of *betula* species were extended to the Trans-Himalaya area 35,000 years ago (Ranhotra et al., 2007). During interglacial and glacial eras in Europe, similar migrations of oak species from the Mediterranean to the boreal regions have been observed [29].

While temperature is viewed as a key factor in limiting species ranges above tree lines (Holtmeier, 2009), precipitation may play a larger influence in changing climatic conditions (IPCC AR4, 2013). The findings indicate that species are migrating to higher elevations, where precipitation is expected to increase significantly. Studies employing dendrochronology show that species growth at lower elevations in both dry and wet zones is decreasing, whereas growth at higher elevations in the wet portion of the central Himalaya is growing [39]. As a result, an overlap in the climatically suitable area for alpine and temperate species is plausible. Overall, changes in the types of species assemblages are expected as a result of (i) the expansion of moist alpine scrub, primarily in the north-central parts of the study region, (ii) the upslope shift and

decline in the range of montane temperate coniferous forests in the east-ern region, and (iii) the placement of moru oak forests above montane temperate coniferous forests in the eastern region, (iv) increasing dom-inance of *R. arboreum* in Deodar and Montane Temperate coniferous forests and (v) loss of assemblages in kharsu oak forest.

Species with higher adaptation in a variety of habitats and the ability to disperse over long distances may be able to track climate change [18]. Conifer tree species in Himalaya are wind-pollinated and depends upon pollen-mediated gene flow via long-distance for maintaining popula-tions. Range fragmentation caused by LULC, on the other hand, may hin-der gene flow between populations, further jeopardizing species' ability to adapt to climate change [63]. In the Himalayan region, LULC has become a major factor in limiting forest areas [2,15]. The findings il-lustrate the need of including LULC data in species range estimates, as the projected region appropriate to maintain a species is often substan-tially larger when simply climate data is used. As demonstrated in the current study, species bioclimatic envelopes paired with LULC data can provide a better understanding of local-level habitat suitability. The re-sults can as well also be used in identifying priority areas to be included in Himalayan ecosystem conservation policy and decision making.

We wish to highlight that the impacts of long term climate change and LULC on the species assemblages have been carried out with some modelling limitations. Since the Himalayan ecosystem is very frag-mented and complex, the impact of climate change on biodiversity will be greatly influenced by land-use change. The distribution of the species and its range shifts due to climate change scenarios will be influenced by its occurrence/existence in the discrete natural patches in the mosaics of natural and managed patches. Hence the existence and distribution of these mosaics in the Himalayan landscape are very important in cap-turing the distribution of the indicator species. So high-resolution LULC change modelling using driver-based trend analysis was adopted in asso-ciation with relatively coarse species distribution modelling. The study highlights that there is a need for the development of high-resolution process-based models for capturing the finer variations in the ecosystem structure as SDM's only explain species spatial distribution and changes due to projected climate changes and do not account for evolutionary processes, as well as a variety of other dynamic processes such as nutri-ent cycling and anthropogenic disturbances such as forest fires, amongst others. Another assumption that has been considered is that the LULC changes which are dynamic and are very difficult to predict for the long term will more or less not vary much between 2055 and 2070 as the various policies such as the adoption of the COP 26 recommendations (November 2021) indicate that the current rate of land-use changes will be minimal by 2050.

Changes in future species distributions will be caused not just by climate change, but also by selective habitat degradation and a gen-eral rise in fragmentation. Our findings show that under current LULC conditions, appropriate habitats for oaks, deodar, and rhododendron are severely fragmented, a finding supported by several other research ([58]; Roy et al., 2013). Because of ongoing and projected changes in the LULC throughout much of the western Himalaya, mid-elevation temper-ate species are the most affected. According to the projected results, an expansion of development activities and LULCC in high altitude temper-ate zones could jeopardize the current distributions of blue pine, deodar

and montane temperate coniferous forests. Due to their proximity to hu-man populations and propensity of exploitation, species including oaks, blue pine, and deodar are anticipated to be the most affected under forecasted scenarios of land cover changes (in conjunction with climate change).

The current study revealed that species assemblages are altering swiftly in a way where present co-existing species disperse and form new co-occurrences under climate change scenarios. As evident, it is unlikely that new species assemblages will emerge without any loss of existing co-occurrences. If species respond to climate change by shrink-ing their distribution size, the chances of new co-occurrences will be even lower. It is difficult to contemplate the consequences that may originate from the disappearance of a large percentage of species inter-actions over a century that took over thousands of years to evolve. The extent to which species are interacting may also change as the unique-ness of interfacing species will also modify. The current study does not answer this question; however, in any way, the breakdown of ecologi-cal balance may occur as a result of the collapse of the mass number of coevolved interactions.

The changes in species assemblages under CC which is going to af-fect the Himalayan forest structure especially moist temperate forests where the dominance of pine (*Pinus roxburghii*) will increase as oak forests shrink (Fig 9–10). This will have severe socio-economic as well as ecological repercussions in the region. The encroachment of Pine into the broadleaved forests [14] will affect the understory species due to the acidification of soil. Pine needles are highly inflammable which is expected to increase the frequency and intensity of forest fires in these regions several folds [3]. This will also result in a reduction in soil mois-ture content and depletion of biodiversity. Furthermore, frequent and recurring fire episodes will result in the depletion of the soil seed banks [28]. Oak/Rhododendron and other broadleaved species are an impor-tant source of livelihood for the communities residing in the Himalayan region and changes in these forest community structures will impact the traditional lives of the local people. The reduction in soil moisture will also impact other aspects of livelihood like agriculture and the availabil-ity of pasture for the livestock.

Data availability statement

The data that support the findings of this study are available from the corresponding author, AR, upon reasonable request.

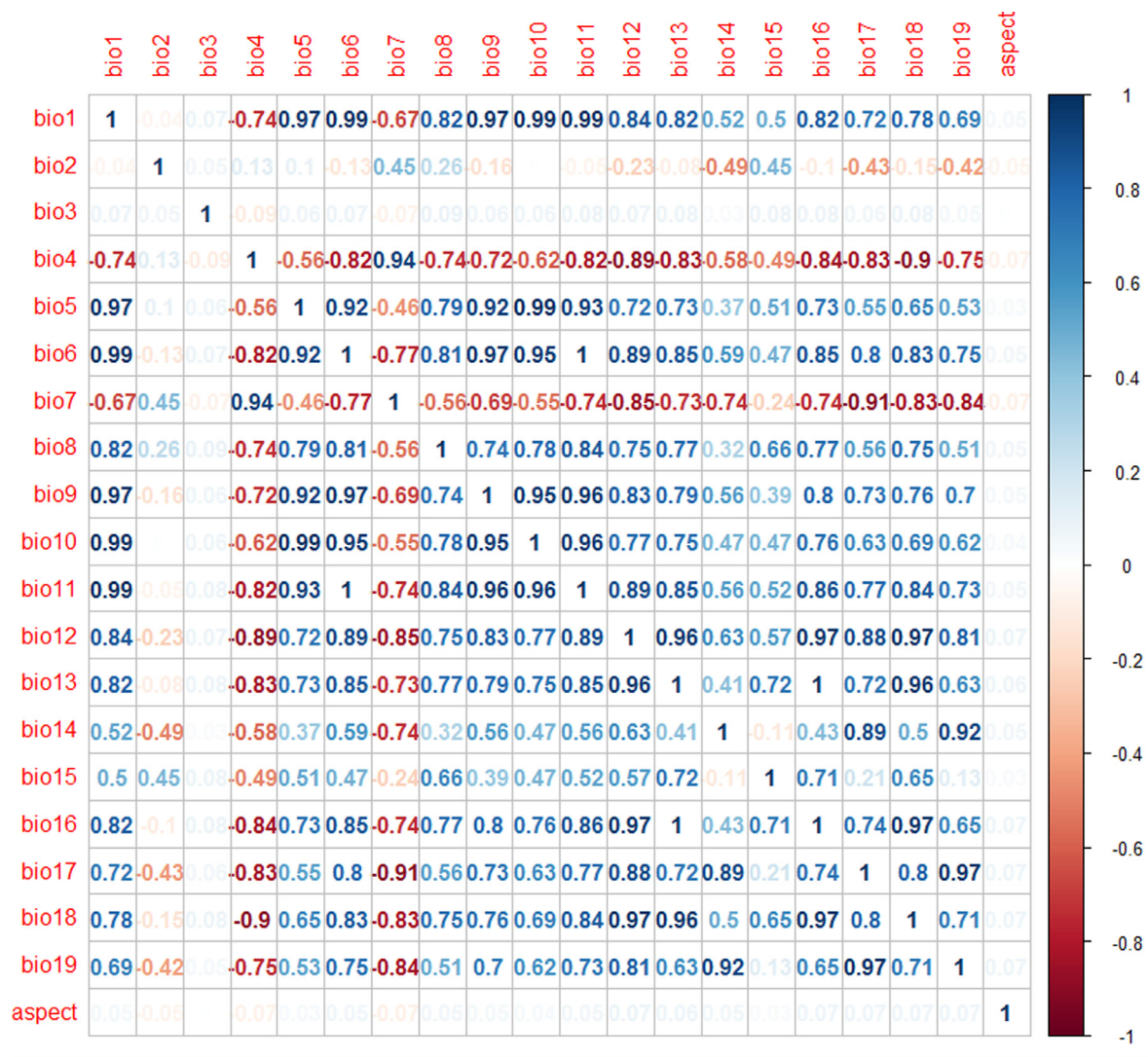### Acknowledgement

Appendix

Figs. A1 and A2.

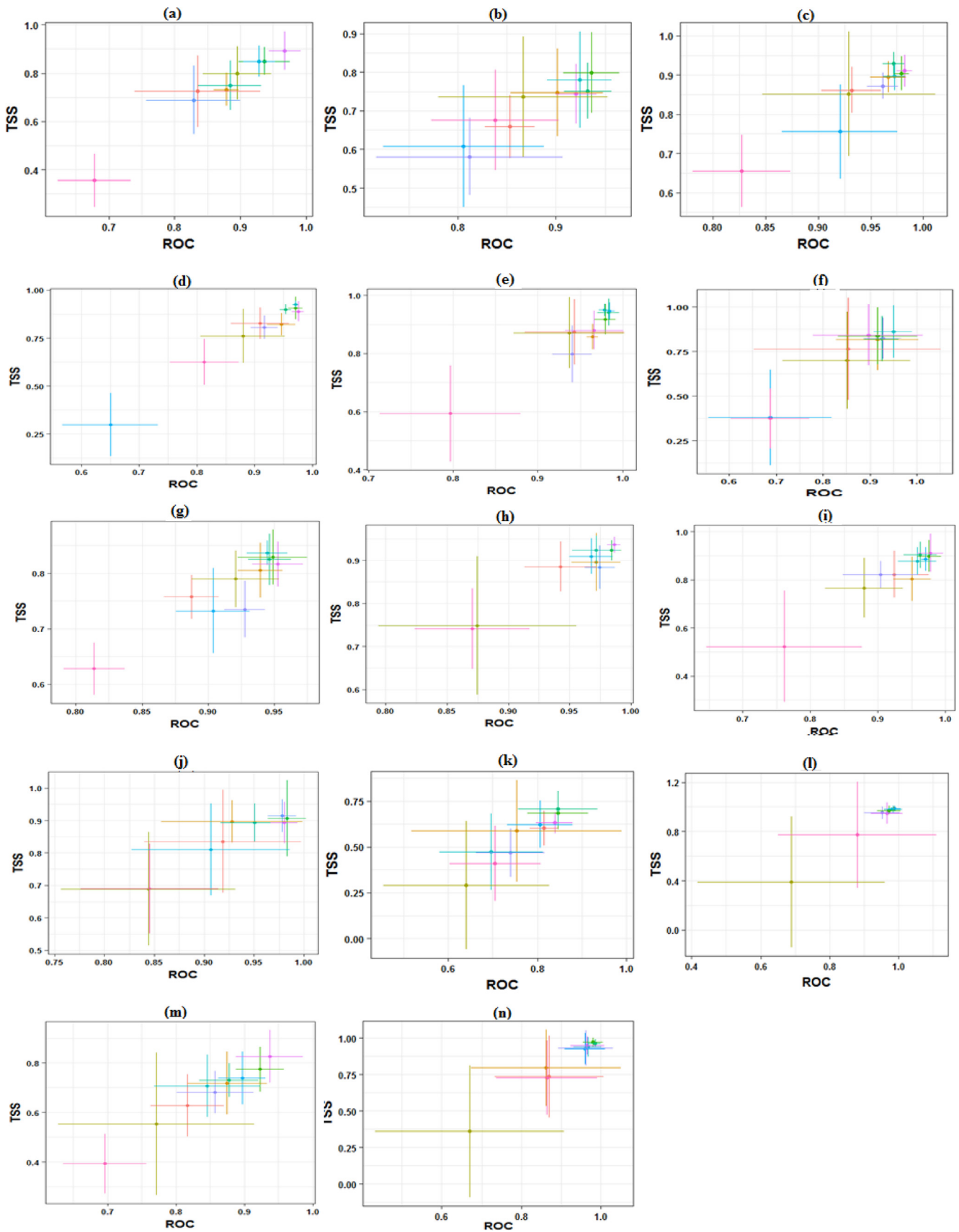**Fig. A1.** Pearson's correlation coefficient matrix between predictor variables.

Fig. A2. Model evaluations for (a) *A. pindrow,* (b) *B. utilis,* (c) *C.deodara,* (d) *P.wallichiana,*(e) *Q. leucotricophora,* (f) *Q.floribunda,* (g) *Q.semecarpifolia,* (h) *R.arboreum,* (i) *P.smithiana,* (j) *T.wallichiana,* (k) *D.hatagirea,* (l) *J. indica* (m) *J.communis,* (n) *L. obovata.*

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