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Climate change impact and vulnerability assessment of forests in the Indian Western Himalayan region: A case study of Himachal Pradesh, India

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ABSTRACT

Climate change impact and vulnerability assessment at state and regional levels is necessary to develop adaptation strategies for forests in the biogeographically vital Himalayan region. The present study assesses forest ecosystem vulnerability to climate change across Himachal Pradesh and presents the priority districts for vulnerability reduction under 'current climate' and 'future climate' scenarios. Vulnerability of forests under 'current climate' scenario is assessed by adopting indicator-based approach, while the vulnerability under 'future climate' scenario is assessed using climate and vegetation impact models. Based on the vulnerability index estimated to present the vulnerability of forests under current and projected climate change impacts representing climate driven vulnerability, five districts – Chamba, Kangra, Kullu, Mandi and Shimla are identified as priority forest districts for adaptation planning. Identifying vulnerable forest districts and forests will help policy makers and forest managers to prioritize resource allocation and forest management interventions, to restore health and productivity of forests and to build long-term resilience to climate change.

Introduction

Forest ecosystems play an important role in the global biogeochemical cycle and exert significant influence on the earth's climate. The boundaries of forest biomes often closely follow patterns of climatic variables; particularly temperature and/or moisture (Stephenson, 1990). A close link between climate and forests implies that a dramatic change in one will influence the other (FAO Forestry paper, 2013). The paleoecological records indicate that forest vegetation has the potential to respond within years to a few decades of climate change (IPCC, 2014). Fischlin (2007) report that 20–30% of the plant and animal species would be at increased risk of extinction if the global average temperature increase exceeded 2–3 °C above the

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pre-industrial level. According to IPCC (2014) climate and non-climate stressors are projected to impact forests during the 21st century leading to large-scale forest die-back, biodiversity loss and diminished ecological benefits.

Climate change is projected to be a dominant stressor on terrestrial ecosystems in the second half of the 21st century, particularly under high emission scenarios such as RCP6.0 and 8.5 (IPCC, 2014). In high altitude and high latitude terrestrial ecosystems, climatic changes exceeding those projected under RCP2.6, will lead to major changes in species distributions and ecosystem function (IPCC, 2014). The vulnerability of forest ecosystems to climate change, i.e. their propensity to be adversely affected, is determined by the sensitivity of ecosystem processes to the particular elements of climate undergoing change and the degree to which the system (including its coupled social elements) can maintain its structure, composition and function in the presence of such change, either by enduring or adapting to it (IPCC, 2014).

In India, national level assessment studies for impact of climate change on forests are available (Chaturvedi et al., 2011; Gopalakrishnan et al., 2011). However such studies are lacking at the regional level. Using climate projections of the Regional Climate Model of the Hadley Centre (HadRM3) and the dynamic global vegetation model IBIS for A2 and B2 scenarios Chaturvedi et al., 2011 have reported that 39 and 34% of forest grids in India are likely to undergo change of forest type under the A2 and B2 scenarios, respectively by the end of this century. This study also concluded that the upper Himalayas, northern and central parts of Western Ghats and certain parts of central India are most vulnerable to projected impacts of climate change, while North-eastern forests are more resilient.

Despite intensive research efforts and planning of adaptation measures for forest management, it remains challenging to take into account the anticipated climatic conditions over the 21st century. This is because: (1) there is still considerable uncertainty about the future climate development and the current climate projections are characterized by uncertainty about the projection of future climate variability and extreme events; and, (2) the existing impact assessments vary widely depending on the impact models applied and climate scenarios investigated.

Himalayan ecosystems are projected to be extremely sensitive under future climate (Chaturvedi et al., 2011). As a part of the Himalayan mountain ecosystem, Himachal Pradesh hosts a wide range of natural resources. The state has unique forests and diverse habitats with large altitudinal variations. Any change in temperature or rainfall pattern will adversely impact the entire ecosystem. Further, Himalayan ecosystems are highly vulnerable due to the stress caused by forest land diversion, increasing pressure from human population, exploitation of natural resources, infrastructure development, mining, and other related challenges. The effect of these current stressors is likely to be exacerbated due to climatic changes, which would be additional (Ravindranath et al., 2006).

Analysis of temperature trends in the Himalayan region shows that temperature increases are greater in the uplands than that in the lowlands (Shrestha et al., 1999). Observed impacts of historical trends include movement of apple orchards to higher altitudes, loss of certain tree species, drying of traditional water sources, changes in bird types and populations, reduction in crop yields, and increased vulnerability of winter cropping due to changes in rainfall patterns and planting dates (ADB, 2010). District level mapping of Himachal Pradesh using a composite of biophysical, social and technological indicators (1960–1990) showed lowest adaptive capacity for Chamba and Kullu and highest adaptive capacity for Kangra, Hamirpur, Una, Solan and Sirmour districts (O'Brien et al., 2004). The districts of Hamirpur, Una, Solan, Bilaspur and Sirmour have been categorised as highly exposed and vulnerable towards climate change whereas, Kullu and Shimla have medium level of vulnerability (O'Brien et al., 2004).

In the present study, we assess vulnerability of forests under current climate scenario (also referred to as 'inherent vulnerability' of forests – Sharma et al., 2013) and climate change driven vulnerability under future climate scenario. All the twelve districts in Himachal Pradesh are ranked according to vulnerability of forests under the two scenarios. We use indicator-based vulnerability assessment methodology under current climate scenario. CMIP5 (Coupled Model Inter-comparison Project phase 5) models-based climate projections under different RCPs and IBIS (Integrated Biosphere Simulator) dynamic vegetation model are used to assess the climate change driven vulnerability under future climate scenario. Such information is useful to prioritize the most vulnerable districts and to develop adaptation strategies and practices in order to build long-term forest resilience to climate change. The following specific research questions are addressed in the present study.

a) What is the forest vulnerability ranking of different districts in Himachal Pradesh under 'current climate' scenario?
b) Forests in which districts are likely to be impacted under 'future climate' scenario?
c) Which are the priority districts for adaptation planning under impending climate change?

Study area: Himachal Pradesh

Geography and location

The hilly, mountainous forests of Himachal Pradesh nested in the Indian Himalayan region (IHR) are spread across three climatic zones namely, the outer Himalayas, the inner Himalayas, and the Alpine zone. It is located between latitude 30° 22′ to 33° 12′ N and longitude 75°45′ to 79° 04′ E. The altitude of the state varies from 248 m to 6735 m above the mean sea level and the total geographical area is 55,673 km^2 (Fig. 1).

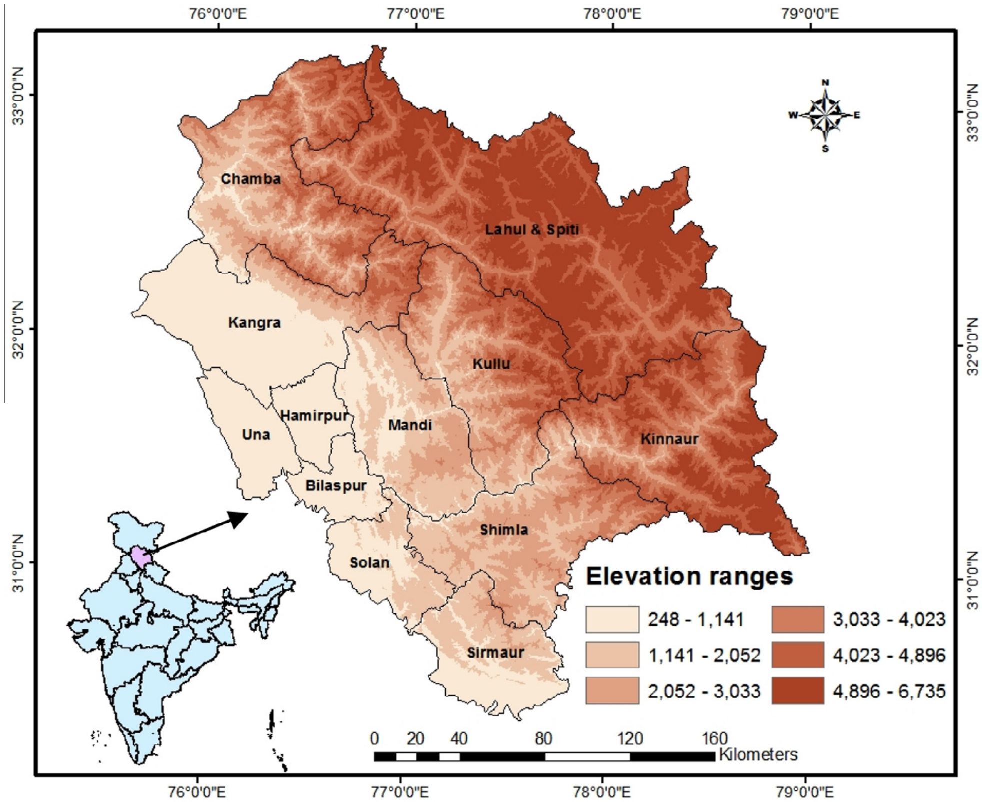


Fig. 1. Location of the study area.

Forest types and status of forest cover

Forests in Himachal Pradesh are an important ecological resource and majority of the people in rural areas depend directly or indirectly on forests for their livelihoods. At present, 26% of the total geographical area of the state is under forest cover with 3224 km^2, 6381 km^2 and 5078 km^2 of the forests having very dense (>70% canopy density), moderately dense (40–70% canopy density) and open forests (10–40% canopy density), respectively (Fig. 2). These forests are classified under eight forest type groups namely, Tropical Moist Deciduous forests, Tropical Dry Deciduous forests, Sub-tropical Pine forests, Himalayan Moist Temperate forests, Himalayan Dry Temperate forests, Sub-Alpine forests, Moist Alpine Scrub and Dry Alpine Scrub (Forest Survey of India, 2013) (Fig. 2).

Methods and models

In this section the methods and models used for assessing the climate change impact on forests and vulnerability are presented. Vulnerability is assessed under two scenarios namely, 'current climate' scenario and 'climate change impacted' scenario.

Approach and methods for vulnerability assessment under 'current climate' scenario

We have adopted "starting-point approach" to understand and assess the vulnerability of forests under 'current climate' scenario (Kelly and Adger, 2000). Under this approach, the present internal state of forests is analyzed (Brooks, 2003) by using appropriate indicators to assess the propensity of forests to suffer losses under future disturbances (Sharma et al., 2015). The results of the assessment are efficiently communicated through a 'vulnerability index' value. Our methodology to assess vulnerability of forests under current climate scenario is based on the methodology reported by Sharma et al. (2015). The details of the methodology steps are as follows.

1. The factors that determine current vulnerability of forests were identified based on literature (Gopalakrishnan et al., 2011; Sharma et al., 2013) and the following indicators were selected for vulnerability assessment namely, biological richness, disturbance index, canopy cover, ground slope, and forest dependence of rural communities. Weights were

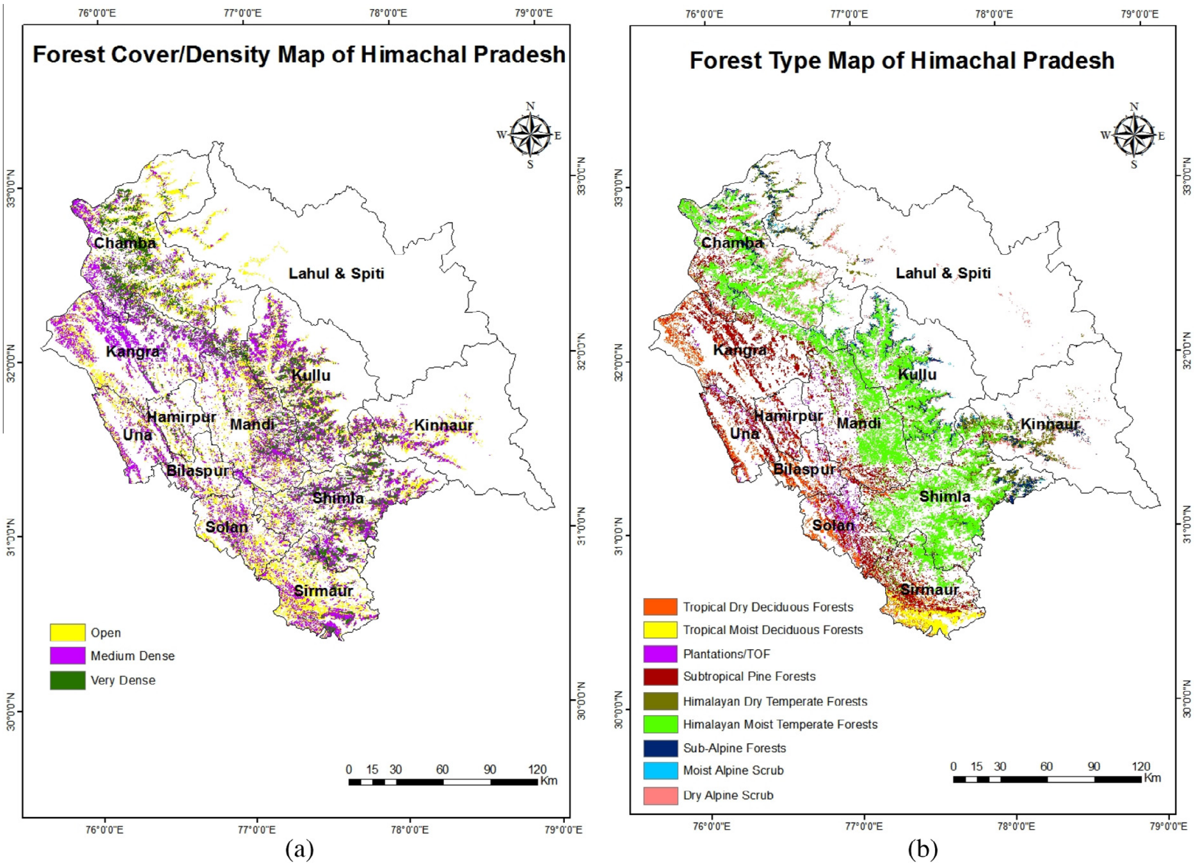


Fig. 2. Forests in Himachal Pradesh: (a) Distribution of open, medium dense and very dense canopy cover forests; and (b) Distribution of different forest types.

assigned to each of these indicators using pair-wise comparison method (PCM) with a Consistency Ratio (CR) of 7.85% (Wang et al., 2008). A Consistency Ratio of <10% is acceptable (for details on PCM and consistency ratio refer to Saaty, 2008). A summary description of indicators and their weights are presented in Table 1.

2. Entire area of the state was divided into 2736 grid cells of $2.5' \times 2.5'$ each. Out of these, 1865 are forest grid cells. Remaining 871 are classified as non-forest grid cells as they do not have any area under forest cover.
3. The spatial data on the indicators was obtained from the databases maintained by the Indian Institute of Remote Sensing (IIRS), Forest Survey of India (FSI) and Government of India (Table 1). The values for an indicator were first grouped into three classes namely low, medium, and high vulnerability class and assigned the values 1, 2 and 3, respectively. For example, the values for canopy cover, which are available in three density classes namely >70%, 40–70% and 10–40% are assigned vulnerability value of 1, 2 and 3, respectively. Then the area-weighted vulnerability-class value (VCV) for an indicator for a grid cell was obtained as sum of the products of the proportion of area of the grid cell under different vulnerability classes and vulnerability-class values (3-high, 2-medium, and 1-low vulnerability) (Eq. (1)). Followed by this, vulnerability for a grid cell contributed by an indicator was obtained as the product of VCV and weight of the indicator (Eq. (2)). Finally, the vulnerability values for all the indicators at a grid cell were added to obtain the vulnerability value at that grid cell (Eq. (3)).

$$\mathrm{VCV}_{ij} = (P_{ij1} \times 1 + P_{ij2} \times 2 + P_{ij3} \times 3) \tag{1}$$

$$\mathrm{VV}_{ij} = (\mathrm{VCV}_{ij} \times W_i) \tag{2}$$

$$\mathrm{VV}_j = \sum_{i=1}^{4} (\mathrm{VV}_{ij}) \tag{3}$$

VCV_{ij} is the vulnerability class value for ith indicator in jth grid cell; P_{ij1}, P_{ij2} and P_{ij3} are the proportions of the area of a grid cell under vulnerability classes 1, 2 and 3 for ith indicator in jth grid cell; W_i is weight for ith indicator; VV_{ij} is vulnerability value for ith indicator in jth grid cell; VV_j is vulnerability value for jth grid cell. (Adopted from Sharma et al., 2015).

Table 1
Details of indicators, indicator components, data sources and weights assigned.

Indicator	Indicator components	Indicator description	Source of data	Weights*
Biological richness (BR)	Species richness terrain complexity ecosystem uniqueness biological value disturbance index	Value of BR for a pixel (24×24 m^2 area) denotes status of biodiversity and potential to host biodiversity in a pixel; higher potential stands for higher resilience and lower vulnerability. DI as part of BR accounts for level of stress on biological richness and capacity of a habitat to host biodiversity.	Indian Institute of Remote Sensing (IIRS) database used	0.507
Disturbance index (DI)	Fragmentation porosity juxtaposition interspersion biotic interference	DI accounts for the change in spatial and structural attributes of forests arising from anthropogenic factors, or anthropogenic and natural factors combined, as compared to undisturbed situation; under disturbed situation species are under new order and competition; forest resilience is adversely impacted.	IIRS database used	0.250
Canopy cover (CC)	Canopy density	Canopy cover is health indicator of forests and change in canopy cover results in change of on-site conditions (exposure) of temperature, desiccation, wind speed and light; loss of canopy cover enhances the exposure and sensitivity of forests and adversely impacts adaptive capacity thus adding to inherent vulnerability.	Forest Survey of India (FSI) database used	0.137
Slope (S)	Ground slope	Propensity to landslides, soil disturbance and erosion due to higher ground slope enhances 'inherent vulnerability' of forests	Open access digital elevation data used	0.035
Forest dependence of rural communities (FD)	Rural population density per sq. km of forest area	Removal of leaf, fuel wood and other biomass impacts productivity and health of forests; seed removal impacts regeneration status; movement of people and cattle propagates disturbance and facilitates proliferation of invasive species and thereby adds to 'inherent vulnerability' o forests.	Census data 2011by the Government of India and FSI data used	0.071

* Weights are assigned using Pairwise Comparison method (PCM) with a Consistency Ratio (CR) of 7.85%. CR of <10% is acceptable (Saaty, 2008).

4. Spatial profile of vulnerability across the state was created by classifying the vulnerability values into four vulnerability classes namely, low, medium, high and very high using the ArcGIS 10.2 Natural Breaks (Jenks Algorithm) program. For district-wise vulnerability profile, the district boundary layer was overlaid on the grid-based vulnerability map for Himachal Pradesh in GIS and value of vulnerability for a district was obtained as the average of vulnerability values for all the grid cells in a district.

Modeling of impact of climate change on forests

In the present study, CMIP5 earth systems model (ESM) based climate projections are used for assessing the impact of climate change on forest ecosystems. Selection of ESMs for assessment of the impact of climate change on forests is dictated by the availability of parameter values required by a vegetation model. DGVMs (Dynamic Global Vegetation Models) simulate time-dependent changes in vegetation distribution and properties, and allow mapping of changes in ecosystem function and services. A number of DGVMs are available to assess the impact of climate change on forest ecosystems. However, in the present study two dynamic vegetation models namely, Integrated Biosphere Simulator (IBIS) and Lund Potsdam Jena (LPJ) are used to simulate the impact of climate change on forests in the state of Himachal Pradesh. With the adoption of multiple DGVMs, uncertainty could be reduced (Alam and Starr, 2013). IBIS model has been used by previous studies (Chaturvedi et al., 2011; Gopalakrishnan et al., 2011) and LPJ is a new model used to simulate the impact of climate change on forests in India. A grid cell size of $0.5 \times 0.5°$ is adopted to simulate climate as well as vegetation projections. However to estimate the number of forest grid cells undergoing forest type shift, grid cells of $2.5' \times 2.5'$, as used for estimating vulnerability under current climate, are considered within a larger grid cell of $0.5 \times 0.5°$ (Table 3).

The climate data requirements for the two vegetation models are very different. While IBIS requires 8 climate variables namely temperature, precipitation, cloudiness, relative humidity, temperature range, wet days, wind speed and deltaT (minimum temperature ever recorded at a particular location minus average temperature of the coldest month), LPJ requires only 3 variables namely, temperature, precipitation and cloudiness. The choice of climate models in the present study was guided by the models used by Chaturvedi et al. (2012) for assessment of climate change in India and the data needs of a vegetation model. Though climate data is now available from nearly 40 CMIP5 models, for IBIS model climate outputs from only five models (BCC-CSM1-1; IPSL-CM5A-LR; MIROC-5; MIROC_ESM and MIROC-ESM-CHEM), which provide all the necessary climate parameters could be used. Data from 17 climate models, which include the five climate models used for forcing IBIS model, was available to force LPJ model, as it requires only three parameters.

The climate change projections are developed for 4 representative concentration pathways (RCPs) scenarios namely; RCP2.6, RCP4.5, RCP6.0 and RCP8.5. However, vegetation projections are simulated under RCP4.5 and 8.5 only. The study presents two time slices – midterm (2021–2050) i.e., 2030s and long term (2070–2099) i.e., 2080s.

Table 2
Ranking of districts on the basis of vulnerability index values under current climate scenario.

District	Vulnerability index (VI) value	Vulnerability ranking of districts	Forest area (km^2)	Rural population per km^2 of forest area
Bilaspur	1.745	3	362	986
Chamba	1.583	9	2437	198
Hamirpur	1.663	7	244	1733
Kangra	1.671	6	2064	688
Kinnaur	1.513	12	600	140
Kullu	1.527	11	1959	202
Lahul & Spiti	1.567	10	194	163
Mandi	1.834	1	1675	559
Shimla	1.682	5	2386	256
Sirmaur	1.701	4	1385	341
Solan	1.749	2	850	558
Una	1.605	8	523	910

Table 3
Number of grid cells projected to undergo forest type shift by both the DGVMs - IBIS and LPJ – in the mid and long term under RCP4.5 and 8.5 according to districts.

District	Total number of grid cells	Number of grid cells projected to undergo forest type shift			
		Mid term		Long term	
		RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Bilaspur	48	0	0	0	0
Chamba	329	109	109	109	248
Hamirpur	28	0	0	0	0
Kangra	253	4	5	5	70
Kinnaur	144	32	32	126	126
Kullu	214	198	203	203	211
Lahul & Spiti	122	93	114	114	120
Mandi	178	51	51	51	72
Shimla	237	120	120	122	122
Sirmaur	140	0	0	0	0
Solan	89	0	0	0	0
Una	83	0	0	0	0
Total	1865	607	634	730	969

In case of IBIS DGVM ensemble mean climatology from five climate models is used to simulate vegetation under future climate. While for LPJ DGVM, the approach has been to make vegetation projections using climatology from 17 climate models individually, one each time, and observe the agreement between (climate) models in simulation of vegetation shift in forest grid cells. The results of LPJ are considered robust when more than 8 models projected the vegetation shift in a grid cell. Forcing the two DGVMs differently with climate data is noted. Nonetheless, comparing and using the simulation results from both the DGVMs is expected to provide more reliable impact assessment compared to when only one model is used (Alam and Starr, 2013).

Methods for vulnerability assessment under 'future climate' scenario

To assess the vulnerability of forests under 'future climate' scenario and to rank the districts according to forest vulnerability, a three-step methodology was adopted. The fulcrum of the methodology rests on combining vulnerability under 'current climate' (or inherent vulnerability, which is assessed by quantifying the factors determining the current sensitivity and adaptive capacity of forests and is independent of exposure – Brooks, 2003) with the future impact (outcome of exposure to climatic hazards). Thus vulnerability of forests under 'future climate' (i.e., climate change driven vulnerability) is equal to the outcome of the effect of exposure from climatic hazards in future imposed on vulnerability under 'current climate'. It is assumed that the vulnerability of forests under 'current climate' (inherent vulnerability) does not change under 'future climate' as the techniques to assess (inherent) vulnerability in future are not available. Details of the steps are as follows.

Step 1: The first step involved assessment of forest vulnerability at district level under current climate scenario (inherent vulnerability of forests). The details of the methodology followed are presented in section 3.1. The outcome of the assessment is forest vulnerability index value for a district.

Step 2: The second step involved assessing the impact of climate change at district level using climate and dynamic vegetation models. The outcome of impact assessment is the number of forest grid cells in a district that are projected to undergo vegetation change and thus impacted under future climate.

Table 4
Vulnerability ranking of districts under future climate scenario in the midterm (2030s) under RCP8.5.

District	Vulnerability index value under current climate (inherent vulnerability)	Ratio of vulnerability index value under current climate (Column 2/ 18.912)	Extent of forest cover (km^2)	Percent forest grid cells projected to be impacted by vegetation modes under RCP 8.5 by 2030s	Forest cover projected to be impacted by climate change (km^2)*	Ratio of forest cover impacted in a district to total forest cover in the state	Future vulnerability index value in the midterm (column 3 + 8)	Rank of a district according to vulnerability of forests in the midterm (2030s)
1	2	3	5	6	7	8	9	10
Bilaspur	1.759	0.093	311	0	0	0	0.0930	8
Chamba	1.546	0.082	2825	33	936	0.182	0.2638	3
Hamirpur	1.562	0.083	167	0	0	0	0.0826	12
Kangra	1.669	0.088	1716	2	34	0.007	0.0949	7
Kinnaur	1.346	0.071	704	22	157	0.031	0.1017	6
Kullu	1.428	0.075	2143	95	2033	0.396	0.4710	1
Lahul & Spiti	1.013	0.054	267	93	250	0.049	0.1022	5
Mandi	1.827	0.097	1563	29	448	0.087	0.1838	4
Shimla	1.682	0.089	2534	51	1283	0.250	0.3385	2
Sirmaur	1.715	0.091	1540	0	0	0	0.0907	10
Solan	1.755	0.093	873	0	0	0	0.0928	9
Una	1.610	0.085	654	0	0	0	0.0851	11
	18.912	1.0	15,299		5,140	1.0		

* It is assumed that the forest cover is distributed equally over all the grid cells in a district.

Step 3: In the third step the results obtained in steps (1) and (2) are combined to rank all the districts in Himachal Pradesh state according to vulnerability of forests under future climate scenario in the midterm i.e., 2030s. To combine the results from steps (1) and (2), the following steps are followed.

a. For each district, the ratio of vulnerability index value of a district and sum of vulnerability index values for all the 12 districts under current climate scenario is calculated (column 3 of Table 4).
b. Extent of forest cover projected to be impacted in a district under climate change (column 7 of Table 4) is calculated as a product of total forest area in a district and the percentage of forest grid cells projected to undergo change under future climate. Followed by this, ratio of the extent of forest cover projected to be impacted in a district and total area of forest cover projected to be impacted in the state is calculated (column 8 of Table 4).
c. Future vulnerability index value for forests of a district is then estimated as sum of the two ratios calculated in step (a) and (b) above (column 9 of Table 4) and ranks are assigned to the districts (column 10 of Table 4). Using the ratios calculated in steps (a) and (b) is valid as the objective is to prioritize the districts by inter-comparison.

Results and discussions

Current vulnerability of forests at district-level

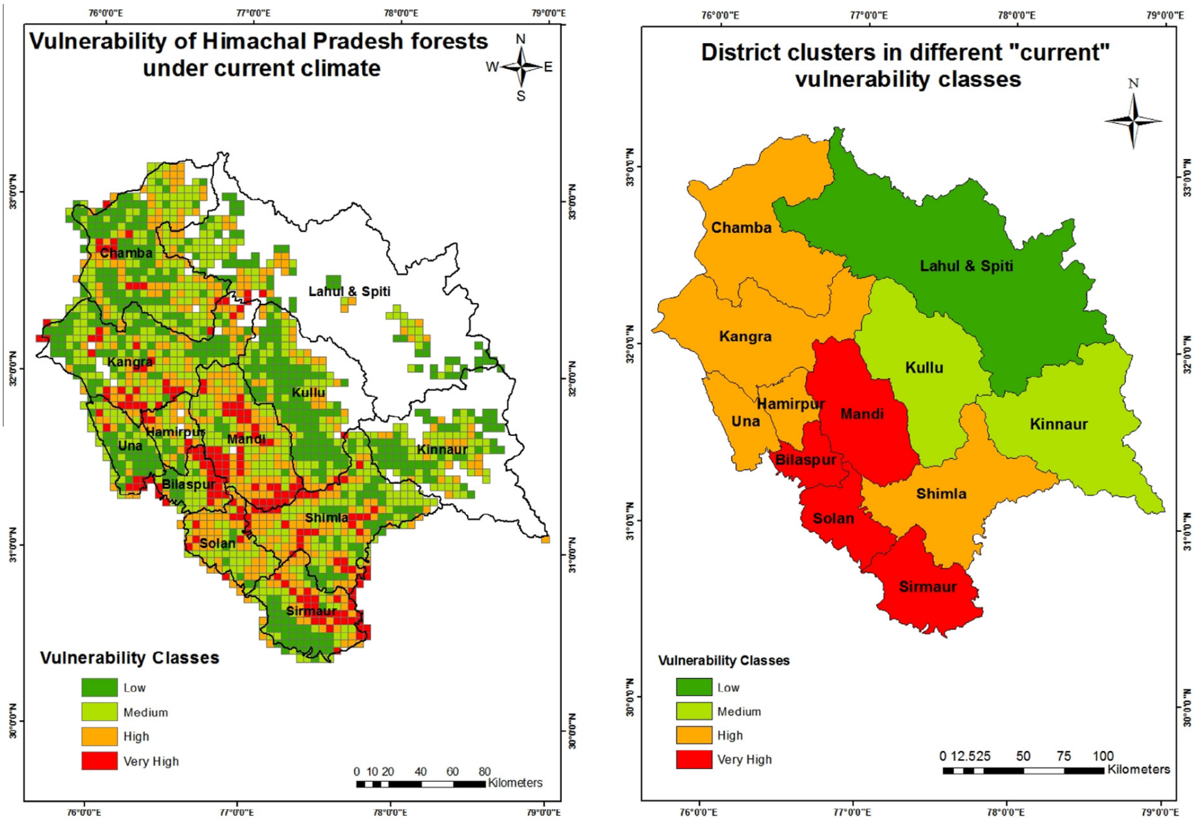
In this Section, the results of assessment of current vulnerability (inherent vulnerability) at district level are presented. Cluster analysis of vulnerability index (VI) values for the districts under current climate suggests the following clustering of districts in different vulnerability classes: Low – Lahul & Spiti; Medium – Kullu and Kinnaur; High – Chamba, Kangra, Shimla, Hamirpur and Una; and, Very High – Mandi, Bilaspur, Solan and Sirmaur. The dominant forest type in Chamba, Kullu, Mandi and Shimla is Himalayan Moist Temperate forests. In Una and Hamirpur Sub Tropical Pine is dominant while Bilaspur is dominated by Tropical Dry Deciduous type of forest. The remaining districts of Kangra, Solan and Sirmaur have a combined population of Himalayan Moist Temperate, Sub Tropical Pine and Tropical Dry Deciduous with Sirmaur also rich in Tropical Moist Deciduous forests. The spatial profile of forest vulnerability and the most vulnerable districts on the basis of vulnerability index values under 'current climate' scenario is presented in the Fig. 3. The details of VI values and ranking of districts as per their vulnerability under current climate scenario are presented in Table 2.

Vulnerability under 'future climate' change

Climate change projections for Himachal Pradesh

CMIP5 based climate change projections for Himachal Pradesh under RCP4.5 and RCP8.5 scenarios for the period 2021–2050 (2030s) and 2071–2100 (2080s) are presented in Fig. 4 for temperature and Fig. 5 for precipitation.

In the midterm (2030s), most districts in Himachal Pradesh are projected to experience a warming of 2–3 °C. However in the long term (2080s), the mean warming under RCP4.5 is in the range of 3 to 4 °C, and under RCP8.5, the warming increases



(a) (b)

Fig. 3. Distribution of forest vulnerability under 'current climate' scenario (inherent vulnerability): (a) distribution of vulnerability at grid cell level (there are no forest grid cells in the area shown in white color; (b) distribution of vulnerability at district level.

to 4–5 °C (Fig. 4). Precipitation is projected to increase by 4–8% under RCP8.5 for most districts in the midterm. The percentage increase in precipitation could be over 16% for all districts, except, Shimla, Mandi, Solan and Una districts by 2080s (Fig. 5).

Impact of climate change on forests

The impact of climate change on forests is assessed on the basis of vegetation shift projected by the two DGVMs - LPJ and IBIS.

Impact according to IBIS DGVM. A spatial presentation of forest shift projected by the IBIS model in the mid (2030s) and long term (2080s) under RCP4.5 and 8.5 are presented in Fig. 6. The outputs from the IBIS model show that in the midterm forests in the districts of Chamba, Kullu, Mandi, Shimla and Kinnaur would be impacted under RCP4.5 and 8.5 and undergo shift from the existing forest type. Further, in the long term forests in the districts of Chamba, Lahul and Spiti, Mandi, Kullu, Shimla, Kinnaur and Kangra would undergo forest type shift under RCP4.5 and 8.5.

Impact according to LPJ DGVM. The results of the climate change impact assessment on forests using LPJ model are presented in Fig. 7. Data from 17 climate models was used one by one to force LPJ model and the simulated impacts were obtained. The impact projections so obtained were overlaid to find the agreement among the impact projections when climatology from different climate models was used. The results presented in Fig. 7 are in terms of the number of climate model outputs used to force LPJ model project impact of climate change at a grid cell.

The Fig. 7 shows that climatology obtained from more than 8 climate models used individually to force LPJ model simulates that the forests in the districts of Kangra, Chamba, Mandi, Kullu, Kinnaur and Shimla would be subject to impact in the midterm under both, RCP4.5 and 8.5. In the long term, forests in the districts of Chamba, Kullu, Mandi, Shimla, Kinnaur, Kangra and Sirmaur are projected to be impacted under RCP4.5 and 8.5 (Fig. 7). More districts and larger area would be impacted under future climate in the long term under both RCP4.5 and 8.5, compared to midterm.

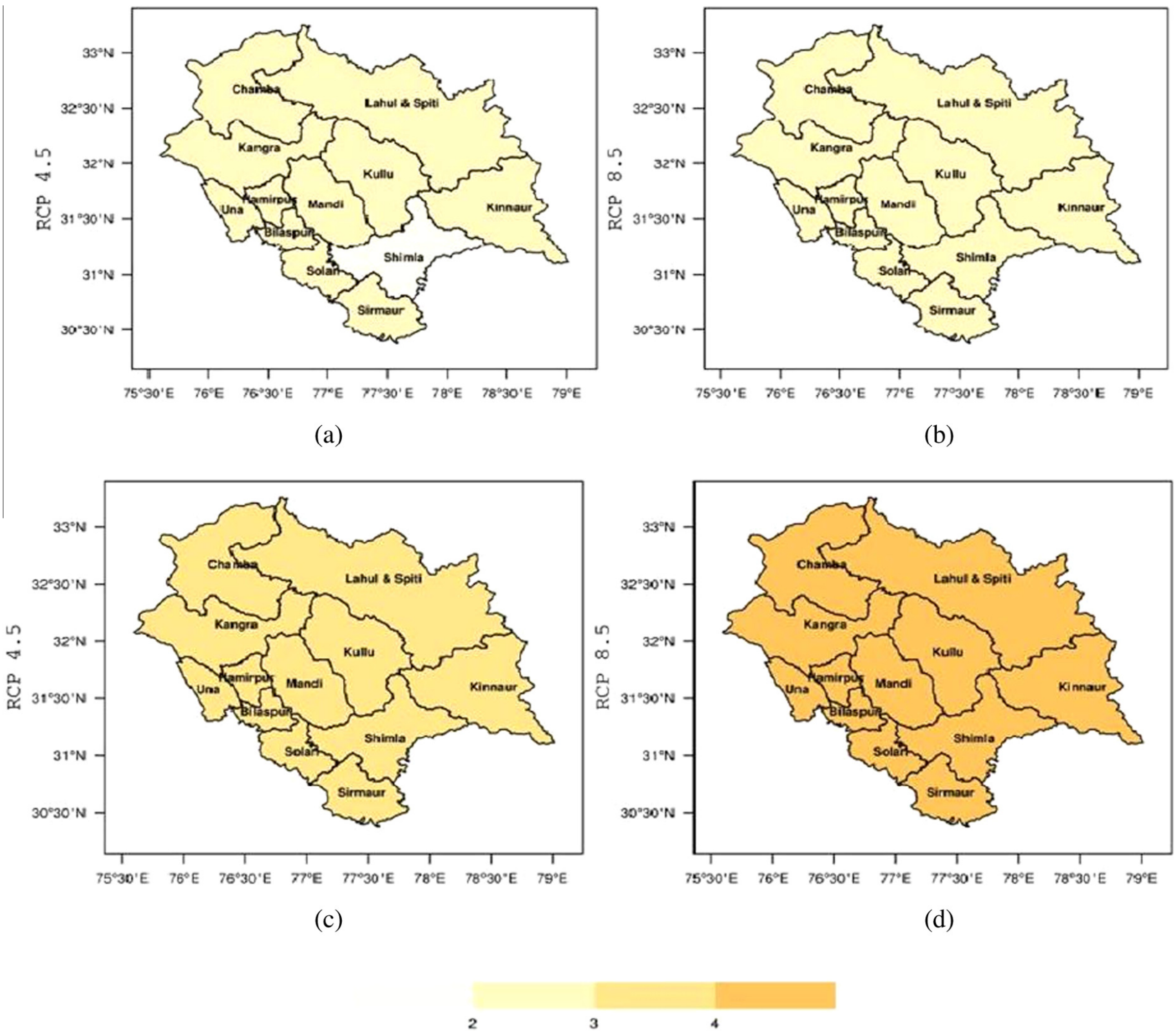


Fig. 4. District-wise projected warming of temperature: (a) for 2030s under RCP4.5, (b) for 2030s under RCP8.5, (c) for 2080s under RCP4.5, (d) for 2080s under RCP8.5.

Grid cells impacted according to both the DGVMs. The difference between the projections by the two DGVMs can be expected because of differing parameterization of physical and biological processes in models. Uncertainties in impact projections are implied when models are used for impact assessments. However, adoption of multiple models improves the reliability of the projections of climate impacts (Alam and Starr, 2013). Agreement between both the DGVMs on the forest grid cells projected to be impacted are likely to be more robust. The model outputs show that the forests in the districts of Chamba, Kullu, Shimla, Mandi, Kangra, Kinnaur and Lahul & Spiti are projected to undergo shifts in forest type by both the vegetation models. The number of grid cells projected to undergo forest type shift by both the DGVMs – IBIS and LPJ – in the mid and long term under RCP 4.5 and 8.5 are presented according to districts in Table 3. In the midterm, 33 and 34% forest grid cells are projected to undergo forest type shift under RCP4.5 and 8.5, respectively; percentage of such grid cells exacerbate to 39 and 52% in the long term. This shows that the future climate will not be optimal for the existing forest types, potentially leading to forest die-back (Cox et al., 2004).

Assessment of vulnerability of forests under 'future climate' scenario

Vulnerability assessment and ranking, considering the combined effect of both the current vulnerability of forests and the impacts of climate change, is useful to identify the most vulnerable districts under 'future climate' scenario. Assuming the current global emissions trend will continue, the focus of present vulnerability assessment is on RCP8.5. We have presented the results of climate change impact assessment on forests according to districts in Table 3. The numbers of impacted grid cells shown in Table 3 are projected to undergo shift by both the models. Forests in Bilaspur, Hamirpur, Sirmaur, Solan and Una districts are not projected to be impacted by both the DGVMs under RCP4.5 and 8.5 during the 21st century. The forests

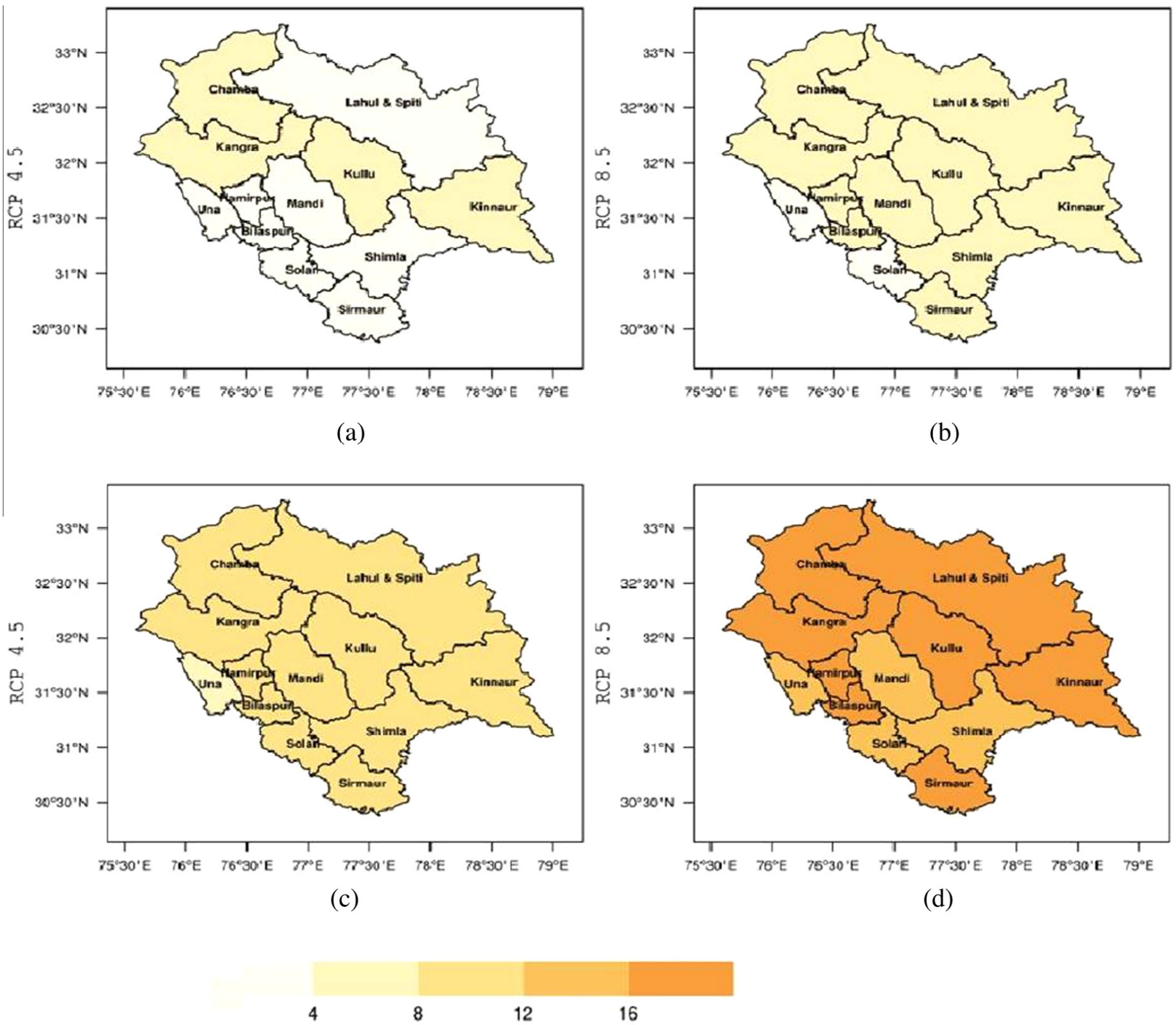


Fig. 5. District-wise projected changes in precipitation: (a) for 2030s under RCP4.5, (b) for 2030s under RCP8.5, (c) for 2080s under RCP4.5, (d) for 2080s under RCP8.5.

in the remaining seven districts would be impacted and the impact would exacerbate in the long term. The major forest districts experiencing high climate change impact are Chamba, Kullu and Shimla.

We have combined the results of climate change impact assessment (Table 3) with that obtained from assessment of current vulnerability (Table 2) to assess the vulnerability of forests under future climate (Table 4). The methodology adopted is explained in section 3.3. As shown in Table 4, districts are ranked according to the future vulnerability index values. A higher value for the future vulnerability index represents higher vulnerability. Accordingly the most vulnerable major forest districts in the midterm under RCP8.5 in descending order of vulnerability are Kullu, Shimla, Chamba, Mandi and Kangra.

Priority districts and adaptation planning

Well-preserved forests are resilient (Noss, 2001; Drever et al., 2006) owing to their high native biodiversity, complex structure and absence of anthropogenic pressures (Thompson et al., 2009). Comparatively, disturbed forests have lower resilience due to factors such as forest fragmentation, poor regeneration and adverse impact of invasive species, and are therefore inherently more vulnerable (Kant and Wu, 2012). Thus under the additional stress from changing climatic factors in future, disturbed forests are likely to experience higher adverse impact than intact forests. The criteria for prioritizing districts for adaptation interventions in the present study include the projected impacts of climate change on forests based on multiple vegetation models and the current vulnerability, which reflects the status of forests (through biological richness, canopy cover and slope) and the socio-economic pressures (through disturbance index and forest dependence of community). Disturbed, degraded and fragmented forests are more likely to be vulnerable to climate change impacts. The DGVMs

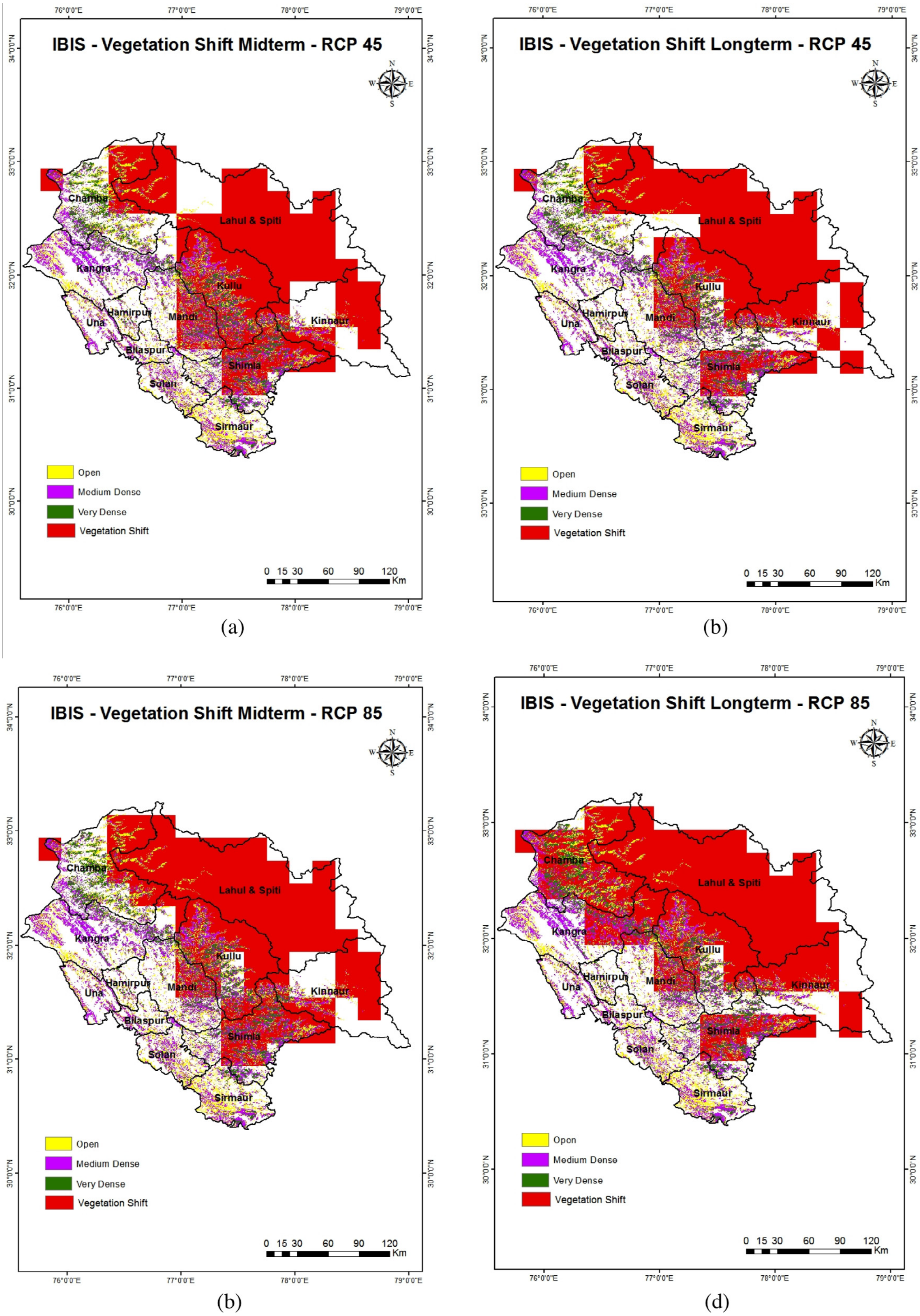


Fig. 6. Vegetation shift projected by IBIS dynamic vegetation model in (a) midterm (2030s) under RCP4.5, (b) long (2080s) under RCP4.5, (c) midterm (2030s) under RCP8.5 and (d) long term (2080s) under RCP8.5.

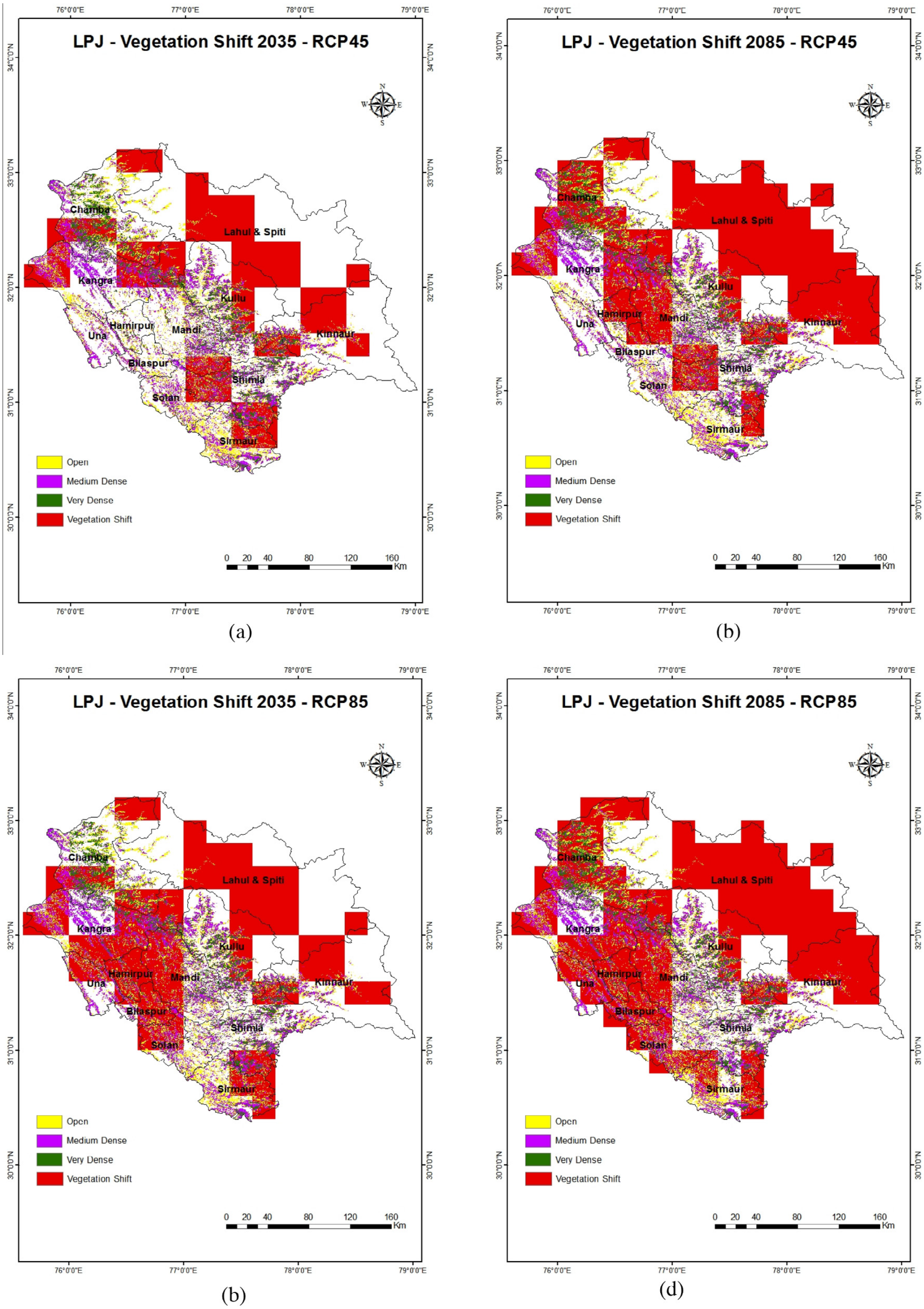


Fig. 7. Vegetation shift projected by LPJ dynamic vegetation model in (a) midterm (2030s) under RCP4.5 (b) long term (2080s) under RCP4.5 (c) midterm (2030s) under RCP8.5 and (d) long term (2080s) under RCP8.5.

do not incorporate these parameters. Thus, a combined vulnerability index incorporating the projected climate change impacts and current vulnerability, as adopted in the present study, is ideal to identify the most vulnerable districts requiring adaptation interventions on a priority basis.

The mountainous forests (Sub-Alpine and Alpine forest, the Himalayan Dry Temperate forest and the Himalayan Moist Temperate forests) are more susceptible to the adverse effects of climate change as climate change is projected to be larger for regions that are at higher elevations (Chaturvedi et al., 2011). The climate change driven vulnerability of forests (vulnerability under future climate) would depend on the extent and rate with which the climate change occurs, the implication of non-climatic stressors, and, the adaptation responses through forest management. Further, uncertainty about the impact of climate change on forest ecosystems, and especially the interspecies interactions, which would determine the future of forests (Boulter, 2012), limit our capability to plan adaptation. Nonetheless, designing management action to restore the fundamental resilience-building mechanisms can help forests regain resilience (Noss, 1999) and improve their performance under climate change.

According to IPCC, 2014), "a first step towards adaptation to future climate change is reducing vulnerability and exposure to present climate variability". Further, tailor-made adaptation strategy for a forest at a given location is necessary because a forest exists in a unique set of conditions pertaining to its ecological importance, current biophysical status, the past history of management, stakeholder dynamics, local customs and traditions, local community-based institutions, and local economy. However, some generic forest adaptation measures include: preservation of all remnant natural forests; limiting anthropogenic disturbances; maintenance and creation of connecting corridors over landscape; supplementing natural regeneration with native species to improve forest stocking and canopy cover; monitoring changes and especially the regeneration of keystone species; fire management and control; and, partnership with communities to limit disturbances and to rationalize forest-use. Forest adaptation measures must be initiated early as they involve gestation period to become effective (Seidl et al., 2009; Kant and Wu, 2012).

Applicability of assessment methodology

In the present study, we have used a novel methodology to assess the vulnerability of forests under future climate by combining vulnerability of forests assessed under current climate (inherent vulnerability) and climate change impact on forests assessed under future climate. For assessment of inherent vulnerability, we have adopted the methodology reported by Sharma et al. (2015), which they have successfully applied to assess the inherent vulnerability of forests in the Western Ghats Karnataka Landscape spread over 4.6 mha. Further, for climate change impact assessments climate and vegetation models are used. It is acknowledged that the climate and vegetation models outputs have uncertainties due to factors such as lack of capability to represent the complexity of Earth's climate system, multiple emission scenarios, and unaccounted ecological and anthropogenic processes. However, despite such uncertainties models remain a useful tool to project the impact of future climate on forest biodiversity and ecosystem services. Use of multiple models can reduce the uncertainty (Alam and Starr, 2013).

Further, difference in projections by the two DGVMs used in the present study does raise questions about the reliability and utility of the results for forest management and decision making. However, we have estimated the impact of climate change on forests by considering the grid cells that are projected to undergo change by both the DGVMs. This enhances the reliability of our results. The methodology used in the study presents a practical option available to prioritize major forest districts in Himachal Pradesh for adaptation planning. The study successfully prioritizes districts. The results of the study would be useful in decision-making. Use of the outcome of vulnerability assessment rests in addressing the current sources of vulnerability to reduce vulnerability and build long-term forest resilience.

Conclusions

The CMIP5 climate models project that most of the districts in Himachal Pradesh will likely experience a mean warming of 4–5 °C and over 16% percentage increase in precipitation in the long term. The forest areas likely to be impacted under future climate are identified using two vegetation models – IBIS and LPJ – based on the agreement between them. A fresh methodology is presented in this study for assessing vulnerability of forests under future climate by combining the information from climate change impacts with the vulnerability under 'current climate', which is represented through future vulnerability index. Based on the future vulnerability index estimated at district level in Himachal Pradesh, the five major forest districts identified as vulnerable districts for planning adaptation interventions are: Chamba, Kangra, Kullu, Mandi and Shimla.

For developing a climate-proofing strategy for forest ecosystems it is useful to consider both, the current vulnerabilities as well as likely impacts on forests under 'future climate' scenario. Integration of information on vulnerability of forest dependent communities and other social, economic and forest management considerations with the biophysical vulnerability of forests is necessary to develop adaptation strategies. Given Himachal Pradesh's unique bio-geographic situation, protecting its rich natural resources assumes greater importance since this would not only impact the very sustenance of the indigenous communities in the mountainous state of Himachal Pradesh but also the downstream agro-ecosystem in the Gangetic plains of India.

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