Indicator-based vulnerability assessment of forest ecosystem in the Indian Western Himalayas: An analytical hierarchy process integrated approach

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ABSTRACT
Understanding the vulnerability of forests and its associated factors is crucial for the sustainable management of forested landscapes. The assessment of vulnerability of forests in the Indian Western Himalayan (IWH) region comprising the states of Jammu & Kashmir (J&K), Himachal Pradesh (HP) and Uttarakhand (UK) was done using six indicators of vulnerability in the form of biological richness index, disturbance index, forest canopy density, fire point intensity and forest extraction intensity of fringe forests. We express this assessment as the “indicator-based vulnerability”. The indicators were allocated weights by multi criteria analysis using analytical hierarchy process. The spatial extent of all of the selected indicators was mapped for the IWH region at a pixel resolution of 24 m and was integrated to find out the vulnerability for each pixel in a GIS environment. The study area was divided into 172 grids of size 0.5°, equivalent to the grid size of available climatic projections, out of which 67 grids were identified as the forest grids. The grids that have at least 5% forest cover were designated as the forest grids and the vulnerability assessment was done only for these grids. The final representation of vulnerability across forested grids of the IWH was done at a spatial resolution of 5° and 0.5° to categorise as low, medium, high and very high class. It was observed that the highest concentration of “very high” and “high” vulnerable grids of 5° size lies in the state of UK, comprising 32 and 31%, respectively. The aggregated values at 0.5° indicate that most of the grids of UK fall under very high vulnerability except for the few uppermost and lowermost grids falling under other categories. In J&K, most of the 5° grids fall under low vulnerability (41%), while medium, high and very high categories are 27, 25 and 7%, respectively. Similarly, out of total 28 grids of size 0.5°, only one grid is categorized as very high vulnerable, while 11 grids fall under high vulnerability. In HP, none of the grids of either size is categorized as very high vulnerable. It was observed that most of the high and very high vulnerable grids in the IWH are in the lower altitudes while higher altitudes have lesser magnitude of vulnerability. Forests occurring at a higher elevation such as the Alpine forests (dry, moist and sub-alpine) is the least vulnerable forests compared to other forest type groups of the IWH.

Keywords:
Forest resource extraction
Disturbance index
Forest fire
Forest management
Climate change

1. Introduction
The vulnerability assessment has been one of the most discussed topics in recent era for the physical, biological and social systems (Cuevas, 2011; Jurgilevich et al., 2017; Nguyen et al., 2017). It has become a central concept in research and policy documents of climate
change (Hinkel, 2011). Recently, the observations related to climate change impacts have increased the policy interests in vulnerability assessment (IPCC, 2007). Considering the importance of the vulnerability assessment for various sectors, the Working Group II of Intergovernmental Panel on Climate Change (IPCC) for its Assessment Reports (AR) (the latest one AR5 published in 2014 and AR6 due for publication by 2021) focuses on the various dimensions of vulnerability in the report titled “Impacts, Adaptation and Vulnerability”. Vulnerability assessment has become the central theme of scholars to examine where, how and why a system would be vulnerable (McDowell et al., 2016; Smit and Wandel, 2006). The vulnerability literature is vast (Giupponi and Biscaro, 2015) and there is a growing interest for assessing vulnerability for environmental and socio-economic disciplines (Gupta et al., 2020; Kalra and Kumar, 2019; Kumar et al., 2019a, 2018a, 2018b, 2020a, 2020b, 2020c; Pokhriyal et al., 2020; Singh et al., 2020).

In 2015, Giupponi and Biscaro published a paper titled “Vulnerability-bibliometric analysis and literature review of evolving concepts”, where they screened existing literature on vulnerability concept by referring to papers of WoS database (>3500) and found the concept used widely for the two streams (1) climate change adaptation, and (2) disaster risk reduction. Here, we present vulnerability assessment of a forest ecosystem which can be used for both of these streams. In the context of climate change, which is a futuristic measure of possible harm, we assumed that a less resilient forest ecosystem (or more vulnerable) in the present context would suffer further due to additional stress of climate change in future. Whereas, with reference to disaster risk reduction we selected the indicators which define the present state of vulnerability varying spatially to identify priority areas of interventions to reduce the propensity of harm. The assessment of vulnerability by us is influenced by the popular definition and concept of vulnerability defined by McCarthy (2001) as “the degree to which a system is susceptible to and is unable to cope with adverse effects”. They suggested a framework in which vulnerability could be measured using three dimensions of Exposure, Sensitivity and Adaptive Capacity of a system under investigation. However, IPCC (2014) framework has delinked exposure and suggest to select indicators that define the sensitivity and adaptive capacity of a system to have a focus on the internal property of a system to withstand the propensity of adverse impacts. This makes the assessment of vulnerability of a system irrespective to the kind of exposure which could be climatic as well as non-climatic. The present assessment adopts a similar concept to measure the internal capability of a forest system through selected indicators elaborated further in the methodology section. The study uses the contextual representation of indicator which has explicitly been explained by Hinkel (2011) as the “media of choice for bridging between academic work and political need”. Accordingly, indicators are useful media to synthesise complex state-of-affairs for vulnerability assessment into a single number that could easily be used in the policy. We selected indicators considering these two clearly defined uses of indicators by IPCC (2014) and Hinkel (2011).

The assessment of vulnerability is context-specific (Füssel, 2007) which has been attempted for various economic, social and environmental sectors including forest ecosystems (Binita et al., 2015; Gupta et al., 2020; Lnya et al., 2017; Nandy et al., 2015; Nguyen et al., 2017; Pokhriyal et al., 2020; Sharma et al., 2017; Yongxiang et al., 2015; Zhang et al., 2017). The plurality of definition of vulnerability has diversified the framework and methodology for assessing vulnerability. However, the indicator-based approach has widely been used (Wang et al., 2008; Zou and Yoshino, 2017) and preferred as these are simple where the measurement is done by assigning a relative weight to multiple indicators that can be used for measuring the vulnerability. The most common approach for assessing vulnerability is the composition of proxy indicators (Luers et al., 2003). Once the indicators are identified their integrated assessment provides an opportunity to preview vulnerability of a system to prevailing and expected scenarios of climate change (O’Brien et al., 2004). There is, however, limited understanding about the vulnerability of a complex system such as the forests of Indian Himalayan Region (IHR). Chakraborty et al. (2018) reviewed the vulnerability of forests in the Hindu-Kush Himalayan region of Asia covering the states of India, Bhutan, Nepal, Bangladesh, China and Myanmar through peer-reviewed articles using WoS and Scopus-indexed publications and found that the knowledge on vulnerability is almost negligible for the forests in the Himalayan region. This indicates the need for developing simple but reliable ways to measure vulnerability which could be adopted for the Himalayan forests across its spread over different countries. Measuring vulnerability is a theoretical concept similar to measuring intelligence, which is not an easy task at all. Nevertheless, the indicators provide an opportunity to develop a scale to measure the vulnerability of a system. Indicators describe the state of affairs of a complex system in simple terms (Barnett et al., 2008; Hammond and Institute, 1995; Hinkel, 2011; Niemeijer, 2002). As the indicators reduce complexity, they are useful in communicating a complex state of a system in a simplified way for the general purpose and use (Hinkel, 2011).

There could be multiple indicators that describe the vulnerability of a system and one need to be cautious while selecting the most appropriate indicators. Assigning weights to the selected indicators is yet another challenge that needs attention. The same system will have a different spatial representation of vulnerability if the assigned weights to the indicators differ. The problem of co-variation and multicollinearity among indicators is often addressed by reducing the number of indicators and selecting only the most relevant ones. Thus, the selection of appropriate indicators is the most essential step for vulnerability assessment. Having discussed facts in mind, we present an...
assessments for measuring vulnerability of a forest ecosystem with the objectives of (1) identification of the most prominent indicators of vulnerability, (2) assigning weights to selected indicators using analytical hierarchy process (AHP) and (3) integration of the indicators to map the spatial extent of vulnerability for a forest ecosystem in the Indian Western Himalayas (IWH). The assessment presented by us, however, must not be considered as the superior approach to simulation-modelling based approach, which is otherwise the most advanced knowledge available to measure the vulnerability of complex systems including forest ecosystems (Hinkel, 2011; Kalra and Kumar, 2019; Kumar et al., 2018a). Nevertheless, we present a simple yet robust approach to map vulnerability using indicators that can be used for other socio-ecological systems, once the appropriate indicators are identified.

2. Materials and methods

The overall methodology used to assess vulnerability can be categorised into three broader steps of (1) selection of appropriate indicators associated with the vulnerability (here forest ecosystem), (2) allocating weights to individual indicators after logical evaluation, and (3) integration of indicators for spatial representation of vulnerability. The methodological steps adopted for the present study is shown in Fig. 1.

2.1. Study area

The study was done for the three Himalayan states of India, viz., Jammu and Kashmir (J&K), Himachal Pradesh (HP) and Uttarakhand (UK) representing Indian Western Himalayan (IWH) region (Fig. 2), covering a total geographical area of 331,392 km² (ISFR, 2019, 2017). Although now the state of J&K has been bifurcated into two separate union territory states of Jammu & Kashmir (western part) and Ladakh (eastern part), however due to unavailability of the boundary maps, the present study uses the definition of the old undivided state of J&K. The mountain ecosystem of the Indian territory lying in these three states of the Himalayas is referred to here as the IWH region. The IWH has varying altitude, producing a very precise pattern of vegetation that includes subtropical forests, conifer mountain forests, alluvial grasslands and alpine meadows. The altitude of the IWH region varies from 500 m to more than 7,000 m (Fig. 3). Being one of the mega-biodiversity hotspots of the world, the region is home to one-tenth of the world’s known higher altitude plant and animal species and half of India’s native plant species, though a large number of species aren’t yet explored (Padma, 2014). The IWH has varying altitude, producing a very precise pattern of vegetation that includes subtropical forests, conifer mountain forests, alluvial grasslands and alpine meadows. The altitude of the IWH region varies from 500 m to more than 7,000 m (Fig. 3). Being one of the mega-biodiversity hotspots of the world, the region is home to one-tenth of the world’s known higher altitude plant and animal species and half of India’s native plant species, though a large number of species aren’t yet explored (Padma, 2014). The IWH has varying altitude, producing a very precise pattern of vegetation that includes subtropical forests, conifer mountain forests, alluvial grasslands and alpine meadows. The altitude of the IWH region varies from 500 m to more than 7,000 m (Fig. 3). Being one of the mega-biodiversity hotspots of the world, the region is home to one-tenth of the world’s known higher altitude plant and animal species and half of India’s native plant species, though a large number of species aren’t yet explored (Padma, 2014).
its land (Fig. 4). Other biophysical and socio-economic characteristics of IWH are highlighted in Table 1.

2.2. Identification and selection of indicators

The selection of appropriate indicators to link with the vulnerability of a system is the most crucial task. The selection of assessment criteria plays a critical role in the evaluation of environment (Wang et al., 2008); therefore, for fixing the indicators, we did comprehensive literature review followed by discussions with peer forest managers and researchers. This helped us to have a better conception of indicators that could be the most fitting ones. The selected individual indicators could be governed by other indicators under consideration. Thus, we first listed the indicators and shortlisted the ones that inherit the property to be qualified as an indicator in the most appropriate way and to a great extent are exclusive to each other. The selected indicators comprised of Biological Richness Index (BR), Disturbance Index (DI), Forest Cover Density (FC), Fire Point Intensity (FPI), Slope (S), Biomass Extraction Intensity of Fringe Forests (BEI).

The BR and DI were procured from the study implemented by Indian Institute of Remote Sensing (IIRS), Dehradun, India for characterising landscape at the national level to identify areas of prioritisation and conservation (https://bis.iirs.gov.in/). These two indices developed by IIRS inherit comprehensively studied multiple factors that could be linked with the spatial variation of vulnerability at the landscape level. The BR is computed by integrating weighted values of (1) uniqueness of an ecosystem (EU) in terms of the presence of localised indigenous and endemic species, and uniqueness defined by the presence of endangered or vulnerable species. Higher the value suggests for a conducive environment to support the endemic species and thus relatively lesser vulnerable system compared to other areas. (2) diversity of the ecosystem described in the terms of Shannon-Wiener Index (H) also referred to as Shannon’s entropy (Shannon and Weaver, 1949) that could be used as a proxy of ecosystem health. (3) economic value (EV) based on the economic and scientific value of the vegetation type. (4) terrain complexity (TC) accounted due to the rate of variation of slope, altitude and aspect in a given window of analysis where higher values signify greater propensity of vulnerability but still supporting diversity. (5) the DI (explained in next paragraph). The BR is calculated as:

$$BR = \sum_{i=1}^{t} EU \times W_{EU} + H \times W_{H} + EV \times W_{EV} + TC \times W_{TC} + DI \times W_{DI}$$

where, $W_{t}$ is the weight assigned to individual components of ecosystem uniqueness (EU), Shannon-Wiener Index (H), economic value (EV), terrain complexity (TC) and disturbance index (DI). The resulting BR was finally categorised into low, medium and high value at pixel level which has been explained in the subsequent section.

The other important indicator identified and retrieved from IIRS database was DI. The DI is calculated by integrating the weighted values of landscape metrics to characterise a landscape to represent the various
levels of associated disturbance by the virtue of spatial arrangements of various land use classes, patch size and their arrangements, usually referred as “landscape metrics”. Landscape metrics play an influential role in guiding the process of a forested ecosystem (Kumar et al., 2019b; Levins, 1968; Turner, 2005) and could be integrated as one of the indicators to evaluate the vulnerability of a system at the landscape level. The DI was calculated by integrating the values of landscape metrics of (1) fragmentation (FR), (2) porosity (PO), (3) number of patches (PN), (4) interspersion (INT), (5) juxtaposition (JUX), and (6) biotic disturbance (B) in terms of distance from the road, settlement, railway track, etc. The DI is calculated as:

$$DI = \sum_{i=1}^{6} FR \times W_{FR} + PO \times W_{PO} + PN \times W_{PN} + INT \times W_{INT} + JUX \times W_{JUX} + B \times W_{B}$$

where, $W_t$ is the weight assigned to individual metrics of fragmentation (FR), porosity (PO), number of patches (PN), interspersion (INT), juxtaposition (JUX), and biotic disturbance (B). Finally, the obtained DI was categorised into low, medium and high value at pixel level as explained in the subsequent section.

A brief explanation of selected indicators, their sources, the methodological framework of calculation and their possible linkages with the vulnerability of the forest ecosystem is summarised in Table 2.

2.3. Assigning weights to the indicators using the analytical hierarchy process

One of the primary steps for the integration of identified indicators is the allocation of weights to respective identified indicators to justify their relative contribution in making the system vulnerable. There could be several approaches while assigning weights, however, the analytical hierarchy process (AHP) developed by Saaty (1977) has widely been used in assigning weights to multiple variables for the environmental, social and sustainability studies (Bantayan and Bishop, 1998; Carver, 1991; Wang et al., 2008). AHP gained wide application in vulnerability studies for the integration of indicators (Khadka and Vacík, 2012; Li et al., 2006; Nicu, 2016; Uddin et al., 2019; Wang et al., 2008; Yuan et al., 2015). AHP provides a framework to quantify relative importance for a set of indicators on a ratio scale that is judged by the evaluators for various alternatives. It is one of the multi criteria based decision making process that uses a hierarchical arrangement of various alternatives to
generate priorities involving the user’s judgement (Saaty, 2000). The major steps involved are explained ahead in the subsequent section.

2.3.1. Assigning relative importance of indicators in vulnerability

The arrangement of identified indicators is done on qualitative scales between 1 and 9 as per Saaty (1980) importance value (Table 3).

2.3.2. Synthesis of pairwise comparison matrix

The construction of a pairwise comparison matrix is done by assigning weights to indicators based on its relative importance as per the Saaty’s importance value shown in Table 3. For example, in Table 4, the first row has BR value equal to BR thus marked as 1, BR compared to DI, FC, FPI, S and BEI is respectively marked as 2, 3, 4, 5, and 7 showing the preference of BR as equally, moderately, moderately to strongly, strongly and very strongly compared to the indicators under consideration. The values of other cells above the diagonal values of 1 have been marked accordingly. Whereas, the lower cells below the diagonal value of 1 represents the relative importance of one variable over other similar to the upper diagonal which is obtained by dividing the value of one indicator by its corresponding indicators under comparison. For example, in the first column, the value of first cell (1.00) is obtained by dividing the value of BR by BR, whereas the 2nd, 3rd, 4th, 5th and 6th cell value is obtained by dividing BR value (1.00) by the corresponding importance value of DI (2.00), FC (3.00), FPI (4.00), S (5.00) and BEI (7.00), respectively. Pairwise comparison matrix of indicators for AHP-derived weights is presented in Table 5. The synthesis of a matrix can be explained as:

$$\begin{bmatrix}
1 & a_{12} & \cdots & a_{1n} \\
1/a_{12} & 1 & \cdots & a_{1n} \\
\vdots & \vdots & \ddots & \vdots \\
1/a_{1n} & 1/a_{2n} & \cdots & 1
\end{bmatrix}_{nm}$$

Table 1

| Parameter                      | Jammu & Kashmir | Himachal Pradesh | Uttarakhand | IWH      |
|-------------------------------|----------------|------------------|-------------|----------|
| General Geographical area (km²) | 222,236        | 55,673           | 53,483      | 331,392  |
| Total forest cover (km²)      | 23,612         | 15,434           | 24,303      | 63,349   |
| Population (million)          | 12.50          | 6.86             | 10.12       | 29.49    |
| Number of districts           | 22             | 12               | 13          | 47       |
| Number of villages*           | 4,939          | 20,690           | 16,793      | 42,422   |
| Land use Pattern (hectare)    | 33.07          | 1,507,522        | 192,077     | 1,699,632.07 |
| Permanent pastures            | 111.94         | 78,791           | 143,619     | 222,521,94 |
| Falling land (current other than current) | 1,096.62        | 64,905           | 387,817     | 453,816,62 |
| Land under miscellaneous tree crop and groves not included in net area sown | 757,450.70 | 543,365 | 700,171 | 2,000,987,70 |
| Net area sown                 | Subzero to 40  | –15 to 43        | –2.4 to 41.5| –2.4 to 43 |
| Climatic parameters           | 600–800        | 1,800            | 1,550       | 600 to 1,800 |

Table 2

| Indicators selected for their integration to map final vulnerability | Brief description of selected indicators and its linkages with the forest ecosystem vulnerability | Data sources/methodology |
|---------------------------------------------------------------------|---------------------------------------------------------------------------------|--------------------------|
| Biological Richness (BR)                                            | BR is computed as a function of ecosystem uniqueness, biological value, species diversity, terrain complexity, and disturbance index. It is a cumulative property of ecological habitat and its surrounding environment. Higher the biological richness, lower the vulnerability of forests or conversely. | Indian Institute of Remote Sensing (IRS) database. (methodology used for mapping BR and DI could be referred from [https://bis.isro.gov.in/methodology-and-approach]). |
| Disturbance Index (DI)                                             | DI represents the inherent vulnerability due to disruption in the proximity of a forest, change in spatial and structural attributes of forests are arising from anthropogenic and natural factors. Higher the value of DI, higher the vulnerability. | Database of Forest Survey of India (FSI) developed for mapping national forest cover. (detail methodology of mapping FC can be referred from [http://www.fsi.nic.in/methodology]). |
| Forest Cover Density (FC)                                           | FC, as an indicator of forest health and vitality, depicts the processes like regeneration and soil dynamics in a forest. FC is influenced by the on-site conditions of temperature, precipitation, wind speed, and light. Denser forest cover indicates better health and lesser vulnerability. | MODIS database obtained from [https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms/active-fire-data] (fire point intensity was represented as the total number of MODIS derived fire points detected during Nov., 2000 to Oct., 2017 at the level of forested grid size of 2.5 x 2.5”, data was processed using ArcGIS 10.1 software). Derived from Shuttle Radar Topography Mission Digital Elevation Model of NASA (SRTM DEM) ([https://earthexplorer.usgs.gov/]) (conversion of DEM into slope was done using spatial analyst tool of ArcGIS 10.1 software) Obtained from the database of Forest Database of Research Institute (FRI), Dehradun, India, developed for a study on “National assessment of forest resource dependence and ecological assessment of forest fringes in rainfed districts of India” (methodological approach could be referred from Kumar et al. [2020b]). |
Table 3
Comparison scale for assigning the importance of indicators in vulnerability
(Saaty, 1980).

| Rating value | Relative importance |
|--------------|---------------------|
| 1            | Equally preferred   |
| 2            | Equally to moderately preferred |
| 3            | Moderately preferred |
| 4            | Moderately to strongly preferred |
| 5            | Strongly preferred   |
| 6            | Strongly to very strongly preferred |
| 7            | Very strongly preferred |
| 8            | Very strongly to extremely preferred |
| 9            | Extremely preferred  |

2.3.4. Assigning final weights to the indicators

The final weight of the respective indicators is calculated as the average value of the rows of the synthesized matrix (Table 5).

2.3.5. Consistency check

The relative importance of one indicator over others might be a random choice therefore the consistency check is done following the method suggested by Saaty (1977). For example, if indicator BR is preferred over DI and DI over FC, then BR must be more preferred over FC. To check this consistency, in AHP, Consistency Ratio (CR) is used for the pairwise matrix generated at Section 2.3.2, which, otherwise, might have been generated as a consequence of the random choice of rating of one indicator to other. CR is expressed as the ratio of Consistency Index (CI) and Random Index (RI), where RI value is taken from the random consistency for the matrix size (in our case matrix size “n” is 6), from the Table 6, which is 1.24, while the CI was calculated following Saaty (1977) as explained below.

CI = \frac{\lambda_{max}}{n} - 1

where \([a_{ij}]\) represent pairwise comparison matrix in which \(a_{ij}\) is 1 and \(a_{ji}\) is \(1/a_{ij}\), and \(i, j\) represent 1,2,3……, n.

2.3.3. Formation of synthesized matrix

Each of the cell values of the pairwise comparison matrix (Table 4) is divided by the sum of the values of their respective rows to form a synthesized matrix (Table 5). The priority vectors obtained at this stage is presented in Table 5.

Table 5
Synthesized matrix.

| Indicators                     | BR   | DI   | FC   | FPI  | S    | BEI  | Weights (W_i) |
|--------------------------------|------|------|------|------|------|------|---------------|
| Biological Richness (BR)       | 0.412| 0.467| 0.424| 0.364| 0.323| 0.333| 0.387         |
| Disturbance Index (DI)         | 0.206| 0.233| 0.282| 0.273| 0.258| 0.238| 0.248         |
| Forest Cover Density (FC)      | 0.137| 0.117| 0.141| 0.182| 0.194| 0.190| 0.160         |
| Fire Point Intensity (FPI)     | 0.103| 0.078| 0.071| 0.091| 0.129| 0.095| 0.094         |
| Slope (S)                      | 0.082| 0.058| 0.047| 0.045| 0.065| 0.095| 0.066         |
| Biomass Extraction Intensity of Fringe Forests (BEI) | 0.059| 0.047| 0.035| 0.045| 0.032| 0.048| 0.044         |
| Total                          | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |               |

\(\lambda_{max} = 6.087, CI = 0.017, RI = 1.24, CR = 0.014 (CR < 0.1 is acceptable).\)

Table 6
Average random index (RI) of consistency for different matrix size (Saaty, 1977).

| Size of matrix | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   |
|----------------|------|------|------|------|------|------|------|------|------|------|
| RI             | 0.00 | 0.58 | 0.9  | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 |      |
The values of $\lambda_{\text{max}}$, CI, RI and CR were obtained as 6.087, 0.017, 1.24 and 0.014, respectively. The CR value less than 0.1 is considered to be as a consistent matrix (Saaty, 1980).

2.4. Integration of weighted indicators and their spatial representation

The integration of indicators for its spatial representation was done through the steps explained below (1–3).

1. The entire study area was divided into grids of 5’ x 5’ for the calculation of vulnerability at this grid size.
2. Thematic layers for each of the indicators were developed using ArcGIS 10.3 keeping pixel size of 24 m. Each pixel was grouped into

Fig. 5. Indicators of vulnerability mapped for the study region: (a) biological richness index, (b) disturbance index, (c) forest cover density, (d) fire point intensity, (e) slope, (f) biomass extraction intensity from the fringe forest.
three classes based upon the magnitude with which they guide vulnerability of thematic group and were categorized as the low, medium, and high vulnerability class pixel value of 1, 2 and 3, respectively. For example, pixels representing forests under 0 to 10-degree slope were assigned the value of 1, 10 to 20° as 2 and slopes > 20 were assigned the value of 3. Steeper the slope higher the vulnerability weight criteria were followed. Pixels of each of the thematic groups were assigned the values of 1, 2 and 3 in similar manner and were identified as P₁, P₂ and P₃.

3. Vulnerability for a grid (VG) was calculated for each of the indicator thematic layers (t) as the sum of the products of the proportion of the pixels under different vulnerability classes of 1, 2 and 3 marked as P₁, P₂ and P₃ (Eq. 1). Vulnerability for a grid cell contributed by the thematic layer (VT) was obtained as the product of VG and weight of the thematic layer (as explained in earlier Section 2.3). Final vulnerability at grid level (Vij) was calculated as the sum of the vulnerability of each thematic layer (Vj) as:

\[ VG_{ij} = (P_{ij1} \times 1 + P_{ij2} \times P_{ij3} \times 3) \]

\[ VT_{ij} = (VG_{ij} \times W_i) \]

\[ V_j = \sum_{i=1}^{k} (V_{ij}) \]

VGij is the vulnerability class value for the jth thematic layer in ith grid cell contributed by proportions of the pixel values low, medium and high classes marked as P₁, P₂ and P₃ respectively. VTij is vulnerability value for jth thematic layer in jth grid cell; Wᵢ is the weight for ith thematic layer; Vᵢ is vulnerability calculated for jth grid cell.

3. Results and discussion

The forested grids of the IWH are presented in Fig. 4. As most of the climate change projections are available at 0.5° spatial resolution (Ahlström et al., 2012; Dufresne et al., 2013; Rogelj et al., 2012), authors have studied the vulnerability of forests under projected climate change scenarios at 0.5° spatial resolution (Upgupta et al., 2015). To have a comparative understanding between the present scenario and projected climate change scenario, the study region was divided into 172 grids of 0.5° x 0.5° size. Among 172 grids, the grids that have at least 5% area occupied by forest were marked as the forest grids (67 number). All of the selected indicators were mapped for forested grids and final assessment of vulnerability was done for the forested grids at 5′ grids as well as 0.5° grids presented in Section 3.2 ahead.

3.1. Indicators identified and their corresponding weights

To assess the vulnerability of a system (including a forest ecosystem), it is important to identify appropriate indicators making the system vulnerable. Once the indicators are identified they could be integrated by assigning proportionate weight through logical evaluation. After a

| Indicators                  | Weights |
|-----------------------------|---------|
| Biological Richness Index (BR) | 0.387   |
| Disturbance Index (DI)      | 0.248   |
| Forest Cover Density (FC)   | 0.160   |
| Fire Point Intensity (FPI)  | 0.094   |
| Slope (S)                   | 0.066   |
| Biomass Extraction Intensity (BEI) | 0.044 |
| Total                       | 1.00    |

Table 7

Indicators selected for the vulnerability assessment and their corresponding weights calculated using analytical hierarchical process (AHP).
A thorough review of the literature and following the expert opinion, six dominant indicators, viz., Biological Richness Index (BR), Disturbance Index (DI), Forest Cover Density (FC), Fire Point Intensity (FPI), Slope (S), and Biomass Extraction Intensity of Fringe Forests (BEI) were mapped (Fig. 5) and were prioritized with respect to each other based on their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7). The weight allocation was done through AHP method of Saaty (1977) where their hierarchical significance in making forest vulnerable (Table 7).

### 3.1. Biological richness index (BR)

The BR mapped for the region is presented in Fig. 5 (a). The BR was categorized into three classes of low (2–33), medium (34–49) and high (50–90) values. Most of the forested region of the study area have medium BR (38.41%). The low and high BR had almost the same spatial extent having 31.91% and 29.68%, respectively. The high BR values were mostly concentrated in the J&K states showing maximum biological richness that need to be conserved.

### 3.1.2. Disturbance index (DI)

The DI map of the region is presented in Fig. 5 (b). The DI was categorized into three classes of low (11–18), medium (19–24) and high (25–90) values. Most of the forest area has high DI spread over 49.57% of the geographical coverage followed by low (19.40%) and medium (31.03%) DI classes.

### 3.1.3. Forest cover density (FC)

Based upon the forest canopy coverage the FC was categorized into low (0–40% canopy density), medium (40–70% canopy density) and high (>70% canopy density) classes. The maximum geographical extent was witnessed for the medium FC (45.84%), followed by low (19.17%) and high (34.99%) FC, respectively. The spatial extent of different FC classes is presented in Fig. 5 (c).

### 3.1.4. Fire point intensity (FPI)

MODIS archived fire points extracted for the period November 2000 to October 2017, to observe the number of fire incidences in a given grid of size 5 x 5', is presented in Fig. 5 (d). It is observed that the number of fire incidences is maximum in Uttarakhand state followed by Himachal Pradesh and Jammu & Kashmir. In a grid of 5' x 5' size, the number of fire incidences over 18 years reaches up to 154 times. 99% geographical area of the forested grids falls under low fire intensity (0–15 times), whereas 9% and 2%, respectively, falls under medium (15–50 times) and high (15–154 times) fire intensity classes.

### 3.1.5. Slope (S)

The slope of the region varies from gentle to very steep, Fig. 5 (e). The forested landscape of study region within forested grids has 32% area under low (0-15') slope class, whereas 38% has a medium (16-30') and 30% has high (>30') slope.

### 3.1.6. Biomass extraction intensity (BEI)

The fringes areas of the forests falling in the vicinity of the villages have maximum extraction pressure. The intensity of extraction quantified at district level suggests that the highest BEI is in Uttarakhand followed by Jammu & Kashmir and Himachal Pradesh. The highest extraction among all districts is in Haridwar district of Uttarakhand (6745.76 t/sq. km/yr) while the lowest is in Lahaul & Spiti district of Himachal Pradesh (0.23 t/sq. km/yr). The BEI of different districts of three states is presented in Fig. 6 and Table 8.

### 3.2. Indicator-based vulnerability of forested grids

All of the indicator layers were first mapped using a pixel size of 24 m, however for the simplicity of presentation and to match the vulnerability mapping with previous studies for the IWH region the assessment was done at a resolution of 5' and 0.5'. Also, the assessment of the vulnerability of forests under projected climate change scenarios have been done at the scale of 0.5′ (Upgupta et al., 2015), hence we also mapped the present state of vulnerability at this scale. The highest concentration of very high vulnerable grids is observed in the state of UK where 32% of its 5' grids fall under this category (Fig. 7 a) with 31% falling under the high category. While 22 and 15% of 5' grids, respectively, fall under medium and low vulnerability, respectively (Fig. 7 b). In the state of HP, none of the grids of either size is categorized as very high vulnerable. Grids of 5' size are categorized into high, medium and low vulnerability except for the few uppermost and lowermost grids falling under low, medium and high category (Fig. 7 b). In the state of J&K, most of the 5' grids fall under very low vulnerability (41%), while medium, high and very high categories are 27, 25 and 7%, respectively. In the state of J&K, out of total 28 grids of size 0.5′, only one grid (grid number 75) is categorized as very high vulnerable, while 11 grids fall under high vulnerability. Whereas, a total number of 7 and 9 (0.5' size grids) have a medium and low vulnerability, respectively (Fig. 7 b). In the state of HP, none of the grids of either size is categorized as very high vulnerable. Grids of 5' size are categorized into high, medium and low vulnerability with 16, 40 and 45% while most of the 0.5’ size grids fall under medium and high vulnerability (9 and 7 in number, respectively) with just a few grids of higher altitudes falling under low vulnerability (3 in number)
It is obvious from the findings that most of the high and very high vulnerable grids in the IWH are concentrated in the lower altitudes while higher altitudes have a lesser magnitude of vulnerability. The study done for the state of HP by Upgupta et al. (2015) for assessing the present state of vulnerability also reported a similar pattern.

3.3. Vulnerability ranking of districts in the IWH

The vulnerability assessment of the IWH region comprising the states of J&K, HP and UK depicts higher vulnerability in the UK comprising the districts of Champawat, Pauri Garhwal, Bageshwar, Almora, Tehri Garhwal, and Dehradun. Very high vulnerability is witnessed in the districts Rajouri, Poonch, and Kupwara of J&K, and Shimla district of HP compared to rest of the districts of the IWH (Fig. 8). Whereas, the districts Kullu, Una, Bilaspur, Kinnaur, Hamirpur, Lahaul and Spiti of HP; Kathua, Jammu, Pulwama, Budgam, Kargil, Leh, Kashmir of J&K; Haridwar and Udham Singh Nagar of UK depict lower vulnerability (Fig. 8). The overall ranking of all of the districts of IWH is presented in Fig. 8.

3.4. Discussion

The assessment of vulnerability of any ecosystem is possible once appropriate indicators are identified. The assessment of present state of vulnerability for the Indian Western Himalayan (IWH) region comprising the states of J&K, HP and UK was done by integrating the spatial extent of selected indicators in a GIS environment. A similar study using different indicators for this region has been attempted earlier by Gupta et al., 2020; Nandy et al., 2015; Pokhriyal et al., 2020; Upgupta et al., 2015, Sharma et al. (2017) did indicator-based vulnerability assessment for entire India by selecting four indicators of vulnerability, viz., biological richness, disturbance index, forest canopy cover density and slope. Upgupta et al. (2015) also used the same indicators to assess vulnerability for the HP state of IWH except for one additional indicator used by us in the form of fire point intensity. Pokhriyal et al. (2020) used ten indicators for the assessment of present vulnerability for the UK state of IWH. They used additional indicators of elevation, aspect, proximity to drainage, road density, average annual rainfall and temperature. In this study, we used six most important indicators after having discussions with experts to consider same indicators as proposed by Upgupta et al. (2015) with an addition of fire point intensity as an important indicator for the IWH region. Studies suggest that steeper slopes, higher levels of fragmentation, and over-exploitation of forests are the major resultant factors responsible for a higher state of prevailing vulnerability (Gupta et al., 2020; Nandy et al., 2015; Pokhriyal et al., 2020; Sharma et al., 2017). Episodic disturbances such as avalanches, wind events, sub-zero temperature for a prolonged duration, insect and pathogen attacks may also act as site-specific stressors while these were not considered for the present study being situational indicators. However, we used indicators that are most prevalent and are the holistic representation of the present state of health of forested grids.

Forested grids of the IWH are unique for each of the altitudinal zones in terms of prevailing climate, the occurrence of dominant species, the frequency of fire and other dominant factors. The assessment of vulnerability in the IWH has been done earlier by researchers to observe altitudinal variations of vulnerability for the socio-ecological set up (Gupta et al., 2020; Nandy et al., 2015). Gupta et al. (2020) assessed the vulnerability of Garhwal Himalayas in the UK state of IWH to observe socio-environmental vulnerability to climate change considering different socio and environmental set up associated with climate change impacts and observed that communities living in middle and high altitudes are more vulnerable. In the present study, the vulnerability of forested grids was observed to be linked with the altitudinal variations in the three states of the IWH (Fig. 9). It is observed that with increasing elevation, the percentage distribution of very high vulnerable grids decreases; where the first zonation of elevation (97 – 1000 m) had maximum percentage of very high vulnerable grids compared to other elevation zones whereas the zone of highest elevation (4000 – 7144 m) did not have such grids. The percentage distribution of different classes of vulnerability in different elevation zones of IWH is shown in Fig. 10.
Fig. 8. Indicator-based vulnerability ranking (decreasing order) of Indian Western Himalayan states at the district level.
The zones between 1000 and 3000 m elevation has a relatively higher percentage of high and very high vulnerable grids counted together, compared to rest of the elevation zones.

The forested grids of the IWH have ten dominant forest type groups (Table 9) among which the highest percentage of grids under very high category is in Tropical moist deciduous forests (52.77%) followed by Subtropical pine forest (25.39%), Himalayan moist temperate forest (17.77%) and tropical dry deciduous forest (17.61%). The least percentage of very high vulnerable grids are in Dry alpine forests (3.11%), followed by Himalayan dry temperate forests (6.28%).

It is concluded that the forests occurring at a higher elevation such as the Alpine forests (dry, moist and sub-alpine) is the least vulnerable forests compared to other forest type groups of the IWH in the present scenario based on the assessment done by considering selected indicators of vulnerability. There are very less such studies available for the IWH region that explicitly demonstrates the vulnerability of different forest type groups, although the studies are available for the vulnerability of some forest type groups. The results suggest that the forests occurring at higher elevations have lower vulnerability compared to those occurring at lower elevations. However, further research is needed to understand the factors influencing the vulnerability of different forest type groups across the IWH region.

Table 9
Indicator-based vulnerability of forested grids across different forest type groups (percentage of grids falling under low, medium, high and very high vulnerability class) in the Indian Western Himalayas.

| Forest Type Groups           | Low   | Medium | High  | Very high |
|-----------------------------|-------|--------|-------|-----------|
| Tropical Moist Deciduous    | 8.69  | 18.31  | 20.23 | 52.77     |
| Dry Deciduous Forests       | 15.95 | 29.59  | 29.06 | 25.39     |
| Subtropical Pine Forests    | 14.83 | 35.32  | 27.04 | 17.77     |
| Subtropical Dry Evergreen   | 32.91 | 26.82  | 35.62 | 4.65      |
| Himalayan Moist Temperate   | 35.15 | 27.42  | 32.31 | 5.12      |
| Himalayan Dry Temperate     | 35.69 | 29.72  | 33.50 | 11.09     |
| Sub-Alpine Forests          | 46.50 | 30.43  | 19.96 | 3.11      |
| Plantation/Tree Outside     | 32.57 | 34.16  | 17.59 | 15.68     |

The percentage of high vulnerable grids is maximum in Subtropical dry evergreen forests (49.49%) and least in Plantation/Tree outside forests (17.59%). The percentage of forest grids of medium vulnerability is maximum in Subtropical dry evergreen forests (35.32%) and least in Tropical moist deciduous forests (18.31%). Dry alpine forests have maximum percentage of low vulnerable grids (46.50%) followed by Moist alpine forests (35.69%), Sub-alpine forests (35.15%), plantation (32.57%), and Himalayan dry temperate forests (32.91%). It is concluded that the forests occurring at a higher elevation such as the Alpine forests (dry, moist and sub-alpine) is the least vulnerable forests compared to other forest type groups of the IWH in the present scenario based on the assessment done by considering selected indicators of vulnerability. There are very less such studies available for the IWH region that explicitly demonstrates the vulnerability of different forest type groups, although the studies are available for the vulnerability of some forest type groups.
4. Conclusions

Human induced factors as well as natural disturbances, both influence the vulnerability of forest ecosystems. Once a clear understanding of the associated factors is established to qualify them as indicators of vulnerability, the vulnerability can be mapped using these indicators. We assessed the vulnerability of forested grids of IWH region using six indicators of vulnerability, viz. biological richness index, disturbance index, forest cover density, fire point intensity, slope of terrain and the biomass extraction intensity. Weights were assigned to each indicators using the analytical hierarchical process (AHP) to integrate each of the indicators to obtain the final vulnerability. Identification of suitable indicators and the allocation of appropriate weights is the foremost prerequisite for mapping vulnerability of a selected ecosystem. We successfully demonstrate a logical way to use indicators to map the vulnerability of forest ecosystems for the IWH region. A similar approach can be adopted for mapping the vulnerability of different regions of the country or the world. Moreover, the methodology as suggested by us in this study may also be used for assessing the vulnerability of other ecosystems such as the agriculture, socio-ecological setup, riparian zones, urban and rural environment, etc. The extent of vulnerability largely depends upon the types of selected indicators and the allocation of weights to each, therefore one should be very much cautious while selecting indicators and assigning weights. The assessment done with different indicators and with a different allocation of weights may differ in the final vulnerability and thus the results may or may not be comparable. Thus, it can be concluded that the selection of indicators and the allocation of weights are the two most important factors for assessing vulnerability.

Forests of the IWH are one of the most precious natural capital upon which survival of the majority of the human population is dependent. However, there are very few studies available for the IWH region that explicitly demonstrate the vulnerability of forest type groups in the present scenario. Therefore, the present study is expected to bridge the gap of the paucity of information. The IWH region represents a diverse and unique ecosystem with many endemic species that are found only in this region. Therefore, any timely available information to observe the regions that may be under a severe state of stress will help the forest managers to implement actions to sustain these valuable resources. The IWH region is also witnessing the implications of climate change and the region is further expected to witness the ill effects of climate change. Thus, it becomes important to identify the regions that are under stress in the present scenario as any impacts of climate change will be additional stress to further deteriorate the situation. Hence, the present study provides timely information to take site-specific actions to preserve valuable resources. The information can be used by policymakers and forest managers to minimise the stress (mapped as vulnerability) of the forests in the IWH region to make them sustainable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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CRediT authorship contribution statement

M. Kumar et al. 125 (2021) 107568

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