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ORIGINAL ARTICLE

Modeling the effectiveness of natural and anthropogenic disturbances on forest health in Buxa Tiger Reserve, India, using fuzzy logic and AHP approach

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Abstract
Forests are the most valuable natural resource to protect organisms as well as ecosystem at a different level. With the rising change of land use and land cover pattern due to anthropogenic and natural disturbances, this resource is now subjected to experience constant exploitation and degradation. This paper explored the level of disturbances on forest health in Buxa Tiger Reserve (BTR), a foothill ecosystem of Himalaya. Sentinel-2 data (2019) and fuzzy logic models were executed to understand the forest health status by using different vegetation indices. GIS-based Analytical Hierarchy Process (AHP) was applied to know the beat-wise spatial disturbances of natural and anthropogenic factors in the study area. Then, disturbance maps were categorized into five zones from very high to very low. The result reveal that overall imprint of natural disturbance in BTR was a little bit high (very high = 13.76%, high = 31.58%, moderate = 15.91%, low = 27.03%, very low = 11.72%) in comparison to anthropogenic disturbance (very high = 11.09%, high = 19.07%, moderate = 24.47%, low = 20.01%, very low = 25.36%), but beat wise it varies significantly. Finally, the effectiveness of both disturbances on forest health was judged through correlation statistics. The forest beats (ID: 2, 4, 6, 7) which cover the core area of BTR have experienced less natural and anthropogenic disturbances with healthy and dense forest cover. On the other hand, less disturbance with poor forest health was found in hilly areas of buxa road and chunabhati beats (ID: 9, 15). Moreover, the effective natural and anthropogenic disturbances were mainly responsible to deteriorate the forest health adequately in most of the areas of BTR.

Keywords Foothill ecosystem · Forest health · Fuzzy logic · AHP · Disturbance

Introduction

Forest has been recognized as a regulator of the biogeochemical cycle on the planet earth and provides explicit and implicit benefits to humans and other organisms. Disturbance affects the functions of ecosystem service and causing a threat to biodiversity; thus, the analysis of factors behind the forest disturbance is a primary concern for the conservationist (Jain et al. 2020; Dale et al. 2001). The impact of human activates on the landscape has been determined by the nature, intensity of disturbance and its effectiveness (Zipperer et al. 1990). Deforestation and degradation of forest resource are an inescapable problem all around the world subsequently due to the extension of agricultural field, urbanization and so on (Ouédraogo et al. 2010). To reduce the negative impact of human activities on natural habitats, in many parts of the world protected areas are delineated to maintain the balance of ecosystem for conservation of wildlife and sustainable utilization of natural resources (Eken et al. 2004; Ikpa et al. 2009). The protected areas like reserve forest are stored more carbon in comparison to its surrounding landscape, the area lost its potentiality due to degradation and deforestation (Scharlemann et al. 2010; Kelatwang and Garzuglia 2006; Dimobe et al. 2015), elsewhere the water and atmospheric circulation of a particular landscape are also nourished by vegetation. Himalaya and its surrounding landscape are highly sensitive to geohydrology; climatic aspects create an impact on the sustainability of the mountainous environment (IPCC 2001; Eriksson 2006; Chen and Lee 2003). Earthquake, landslides, soil erosion, slope failure accelerated by severe rainfall storm are common natural phenomena experienced by this landscape (Alexander 2008;

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Shrestha 1997; Liu et al. 2004; Van Westen et al. 2008; Pande, 2016). The combined action of human and physical stress causes environmental degradation that becomes now a global concern (Byers 1985; Kienholz et al. 1984; Zimmerman et al. 1986). Behind the forest distress, both natural and anthropogenic activities are worked as responsible factors so far (Karanth et al. 2006; Gray et al. 2018; Hérault and Piponiot 2018).

Remote sensing is a powerful tool use to provide information about recognizable features of land cover areas, e.g., vegetation, water, soil, etc. based on spectral reflectance (Sabins 1987; Lillisend and Keifer 2004). It is an important source to monitor vegetation and changes from local to global level (Dimobe et al. 2015; Joshi et al. 2006; Avetisyan 2015; Fritz et al. 2017). Numerous vegetation indices (VIs) are used to measure quantitative and qualitative aspects of vegetation based on the spectral reflectance of the sensor (Bannari et al. 1995). VIs are still the most effective and useful indicators to depict the density and growth status of vegetation by using spectral reflectance especially red and near-infrared ranges (Xiro et al. 2004; Sun et al. 2019; Joiner et al. 2018). Mostly, MODIS, Landsat, Sentinel data are used by researcher to detect biophysical and biochemical characteristics of vegetation (Pearson et al. 1976; Li et al. 2017; Anderson 1993; Liu et al. 2012). The health of wheat crop has been studied by Dimitrov et al. (2019); they established the relationship between biophysical, biochemical variables with remotely sensed vegetation indices using Sentinel-2 data. Lin et al. (2019) have evaluated that how VIs associate with incident carbon flux tower GPP (GPP_{EC}) and photosynthetic active radiation (PAR_{in}) across the forest, grassland sites in Australia. On the other hand, a simple regression model has been used to estimate crop LAI (Leaf Area Index) from VIs retrieve from high-resolution optical remote sensing data (Liu et al. 2012). The free access of Sentinel-2 images is used to quantify canopy LPI and chlorophyll of tropical forest in North India by Padalia et al. (2020). They also tried to find out the correlation between VIs and these two key variables. Gwal et al. (2020) have utilized Landsat 8 OLI data to estimate the NPP (Net Primary Productivity) and biomass quantities in complex Himalayan terrain based on a random forest machine-learning algorithm. Some researcher has also studied on forest cover change analysis based on image classification at different levels (Kennedy et al. 2007; Huo et al. 2019; Healey et al. 2005; Huang et al. 2010; Talukdar et al. 2019). The automated robust algorithm is applied by Ozdogan (2014) for examining the disturbances in the forest with remote sensing. Mitchell et al. (2017) highlighted the role of remote sensing to monitor and report forest degradation for the REDD + strategy. The fragmentation and forest density model been has used by Jain et al. (2020) to detect the disturbance in the Sariska Tiger Reserve of Rajasthan, where undisturbed areas witnessed a decrease due to a significant increase in anthropogenic activities. Pokhriyal et al. (2019) assessed vulnerability in the forested area of Uttarakhand and AHP was used to identify the important drivers of vulnerability.

The Buxa Tiger Reserve (BTR) has gone through many disturbances caused by natural hazards like flood, landslide and human activities via grazing, cutting of trees, mining of boulder and minerals. Thus, monitoring of disturbances become crucial for studying their impact on forest health and manage forest cover efficiently. In this paper, fuzzy logic has been used to monitor forest health at a different level, simultaneously AHP is applied to assess the level of natural and anthropogenic disturbances in BTR. Finally, the assessment of the correlation between forest health and disturbances helps us to detect the effectiveness of disturbances on forest health.

The study area

Buxa Tiger Reserve (BTR) is located in the Bengal Duars region of Eastern Himalayan foothills. BTR has been characterized by dense and multi-tier vegetation assemblage with rich biodiversity. It is extended over a length of 50 km from east to west and 35 km from north to south. The total area of this tiger reserve is 760.87 sq. km., out of which 385.02 sq. km. is under the sanctuary and national park (Das 2012). The northern side of this reserve bounded by Bhutan and Assam borders followed by river Sankosh lies on the eastern side of BTR (Fig. 1). This tiger reserve is situated in the confluence of three bio-geographic zones, Central Himalaya (2C), Lower Gangetic Plains (7B) and Brahmaputra Valley (8A). It has played a significant role to maintain the ecological prosperity of this region. This reserve not only protects the catchments of enormous rivers and streams from soil erosion but also acts as a carbon sink of the region. The downstream irrigation and rich forest resource also help the local people towards economic prosperity.

Materials and methods

Data acquisition and processing

Sentinel-2 satellite with Multi-Spectral Instrument carries 13 bands from visible, near- infrared, to short wave infrared in different spatial resolutions of 10 m, 20 m and 60 m. Sentinel-2 Level-1C (date of acquisition: 30/01/2019) product of the area of interest was downloaded from the Copernicus Open Access Hub (https://scihub.copernicus.eu/). The top of canopy reflectance of the required bands was produced using the Sen2Cor processor and 10 m bands were resampled to 20 m resolution and Red, NIR and Red-edge bands were used accordingly to calculate different vegetation indices.

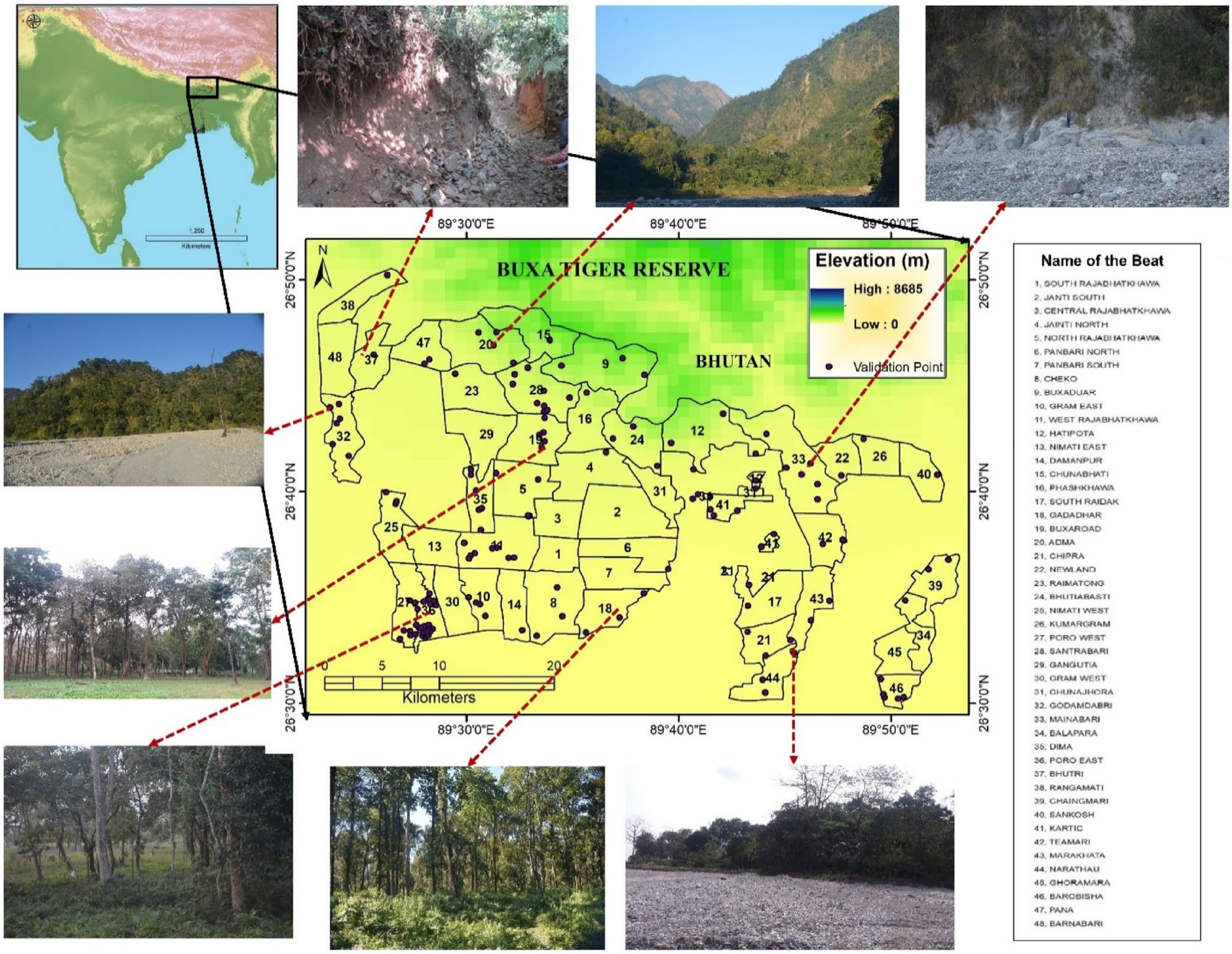

Fig. 1 A glimpse of forest sites in Buxa Tiger Reserve

The forest map of BTR was georeferenced to do a subset of imagers accordingly. Image-to-image co-registration has been performed to ensure better assignment of pixels in the respective images.

More than hundred ground data points were collected by hand-held Global Positioning System (GPS) device and images of Google Earth (2.4 m × 2.4 m) of January 2019 have been also used to train the spectral signature of selected land coved area, specifically the disturbed forested area of BTR. ASTER GDEM2 was chosen to extract variables like elevation and slope. The detailed information about the source of datasets is listed in Table 1. All data are resampled to 30 m resolution in the GIS environment for further analysis.

Generation of criterion maps

Now, remote sensing of vegetation has widely applied where spectral properties of vegetation are used as a proxy to understand the spatial and temporal variations in vegetation structure and density (Tesfaye and Awoke 2019). Specifically, optical properties of NIR, RED and Red-Edge (RE) bands and their correlations are the major indicators of vegetation health. The two-dimensional feature space of NIR and Red in a triangular shape shows healthy coverage of vegetation has high reflectance of NIR and low reflectance in Red band with a longer distance from soil line (Gao et al. 2013); whereas, the band NIR and Red-Edge are also positively correlated (Fig. 2). Vegetation indices are generally classified into two groups, one is slope based and another one is distance based. The slope-based indices include NDVI, SAVI, TVI, RVI, etc. which are generally used widely to know the state and abundance of the greenness of vegetation. Distance-based indices are effective to cancel brightness of soil where vegetation is sparse such as PVI, MSAVI, DVI, AVI, etc. (Silleos et al. 2008). In the present study, eight indices are chosen from both groups to address the

Table 1 Source of different datasets used in the study

Data	Description	Resolution/scale	Source
Vegetation Indices (NDVI, EVI,RVI etc.)	Sentinel-2 Level-1C	10 m/20 m/60 m	https://scihub.copernicus.eu/dhus/#/home
Elevation	ASTER- GDEM	30 m	https://earthexplorer.usgs.gov/
Slope	ASTER- GDEM	30 m	https://earthexplorer.usgs.gov/
Rainfall	Applied spatial interpolation method IDW	30 m	Directorate of Agriculture and Irrigation, WB, IMD, CWC-India
Soil	Digitized from NATMO soil map	1:2,000,000	https://geoportal.natmo.gov.in/
Drainage/river	Extracted from GDEM	30 m	–
Settlement	Digitized from Google Earth Pro	2.4 m	https://www.google.com/intl/en_in/earth/versions/#earth-pro
Transportation	Digitized from Google Earth Pro	2.4 m	https://www.google.com/intl/en_in/earth/versions/#earth-pro
Population	Census of India	2.4 m	https://censusindia.gov.in/

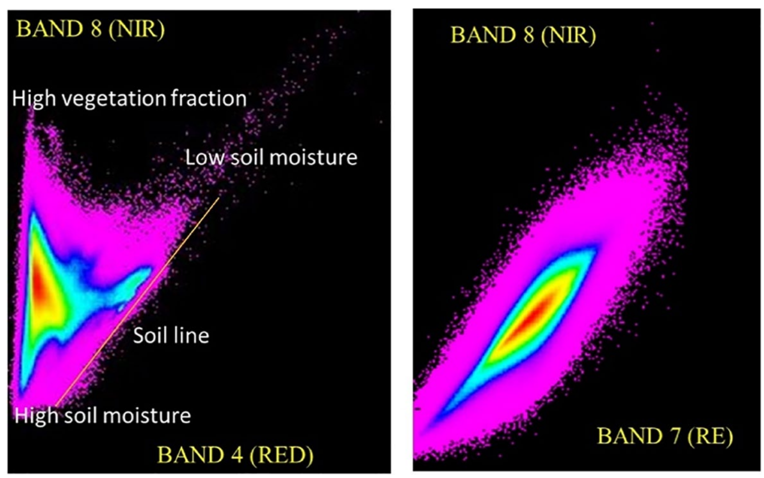

Fig. 2 Feature space responses of NIR, Red and Red-edge bands

Table 2 Detail lookout of vegetation indices

Index	Description	Formula	References
NDVI	Normalized difference vegetation index	$\frac{NIR-RED}{NIR+RED}$	Rouse et al. (1973)
SAVI	Soil adjusted vegetation index	$1.5 * \frac{NIR-RED}{NIR+RED+0.5}$	Huete and Jackson (1988)
TVI	Triangular vegetation index	$\sqrt{\frac{NIR-RED}{NIR+RED}} + 0.05$	McDaniel and Haas (1982)
EVI-2	Enhanced vegetation index	$2.5 * \frac{NIR-RED}{NIR+2.4RED+1}$	Jiang et al. (2008)
RERVI	Red-edge ratio vegetation index	$\frac{NIR}{RE}$	Cao et al. (2016)
DVI	Difference vegetation index	$NIR - RED$	Tucker (1979)
RVI	Ratio vegetation index	$\frac{RED}{NIR}$	Pearson and Miller (1972)
MSAVI	Modified soil adjusted vegetation index	$\frac{NIR + 0.5 - 0.5}{\sqrt{(2NIR + 1)^2 - 8(NIR - RED)}}$	Qi et al. (1994)

stressed and disturbed area of BTR (Table 2 and Fig. 3). After that, fuzzy overlay has been implemented based on those indices to detect the best fittest model of forest health.

The region of Himalayan foothills induced to experience both natural and anthropogenic disturbances. A total eight of disturbance factors are chosen in this study. The criterion maps of disturbance (Fig. 4) has used further in the AHP model.

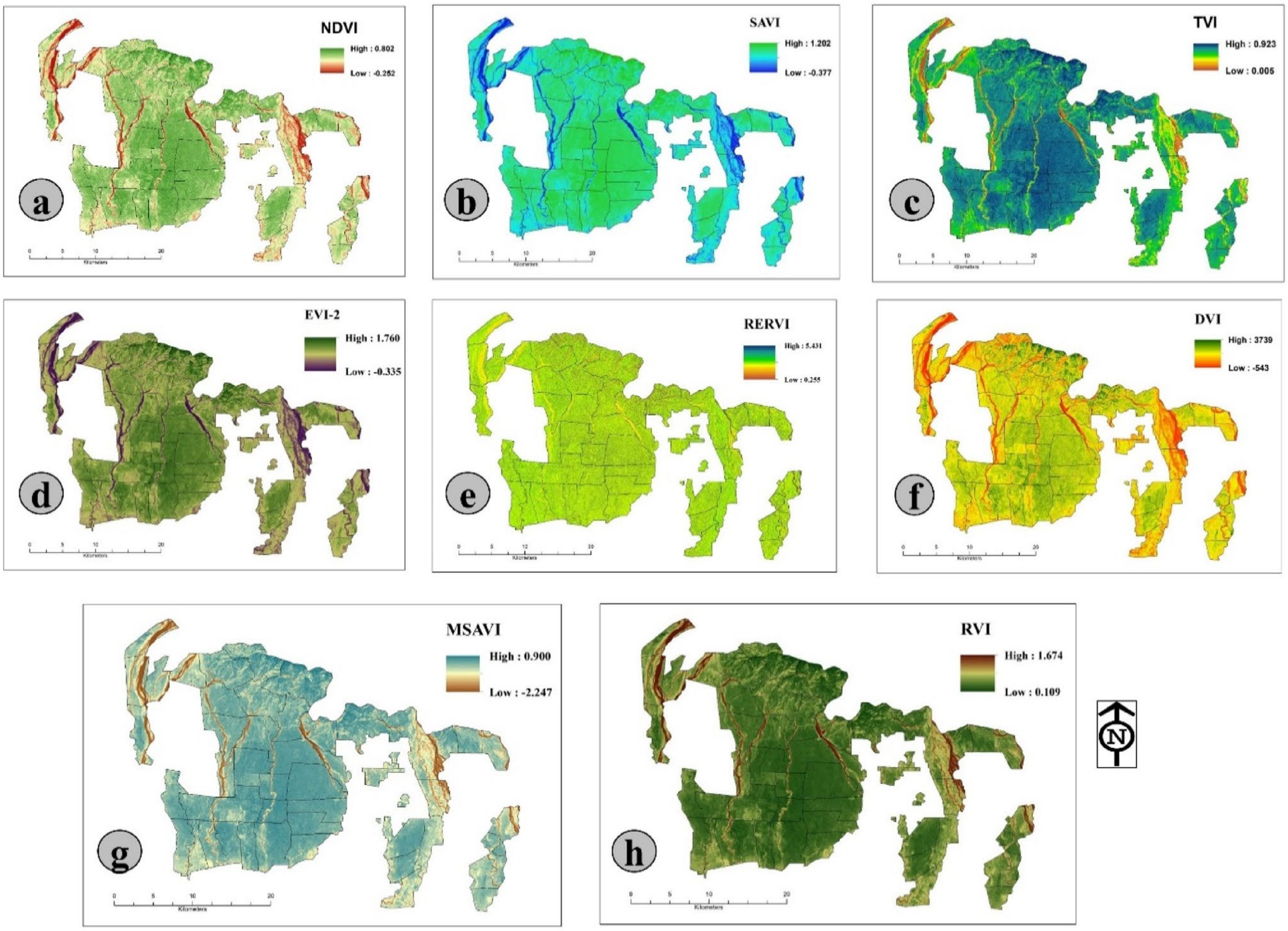

Fig. 3 Spatial view of different vegetation indices in BTR; **a** NDVI, **b** SAVI, **c** TVI, **d** EVI-2, **e** RERVI, **f** DVI, **g** MSAVI, **h** RVI

Fuzzy Logic (FL)

One of the reasonable computing tools to solve complex problems (Huanga et al. 2010) is the Fuzzy set and it was introduced by Zadeh (1965). Fuzzy logic (FL) is unique in comparison to other conventional methods because it allows objects to partially attach with multiple sets and also have multiple values (Donevska et al. 2012). The membership value in fuzzy logic denoting the degree of certainty of a set and the value must lie between 0 and 1. Zimmerman (1996) introduced a different type of combination rules for membership functions. An et al. (1991) and Bonham-Carter (1994) has discussed five fuzzy operators, namely fuzzy SUM, fuzzy AND, fuzzy OR, fuzzy PRODUCT and fuzzy GAMMA.

Fuzzy algebraic SUM is complementary to the fuzzy product operator and defined as:

$$\mu_{\text{combination}} = 1 - \prod_{i=1}^{n}(1 - \mu_i) \tag{1}$$

Fuzzy algebraic PRODUCT operator defined as:

$$\mu_{\text{combination}} = \prod_{i=1}^{n} \mu_i \tag{2}$$

where '$\mu_{\text{combination}}$' is the fuzzy membership function for the ith map, and 'i' = 1, 2,3, …, n maps are to be combined.

The fuzzy AND operator is equivalent to a Boolean AND, defined as:

$$\mu_{\text{combination}} = \text{MIN}(m_{A,} m_B, m_C \ldots .) \tag{3}$$

The fuzzy 'OR' is like the Boolean OR (logical union), and defined as:

$$\mu_{\text{combination}} = \text{MAX}(m_{A,} m_B, m_C \ldots .) \tag{4}$$

where $\mu_{\text{combination}}$ is the calculated fuzzy membership function, 'm_A' is the membership value of map A at a particular location and 'm_B' is the value of map B, and so on.

The fuzzy gamma operator is defined in terms of fuzzy algebraic product and fuzzy algebraic sum as:

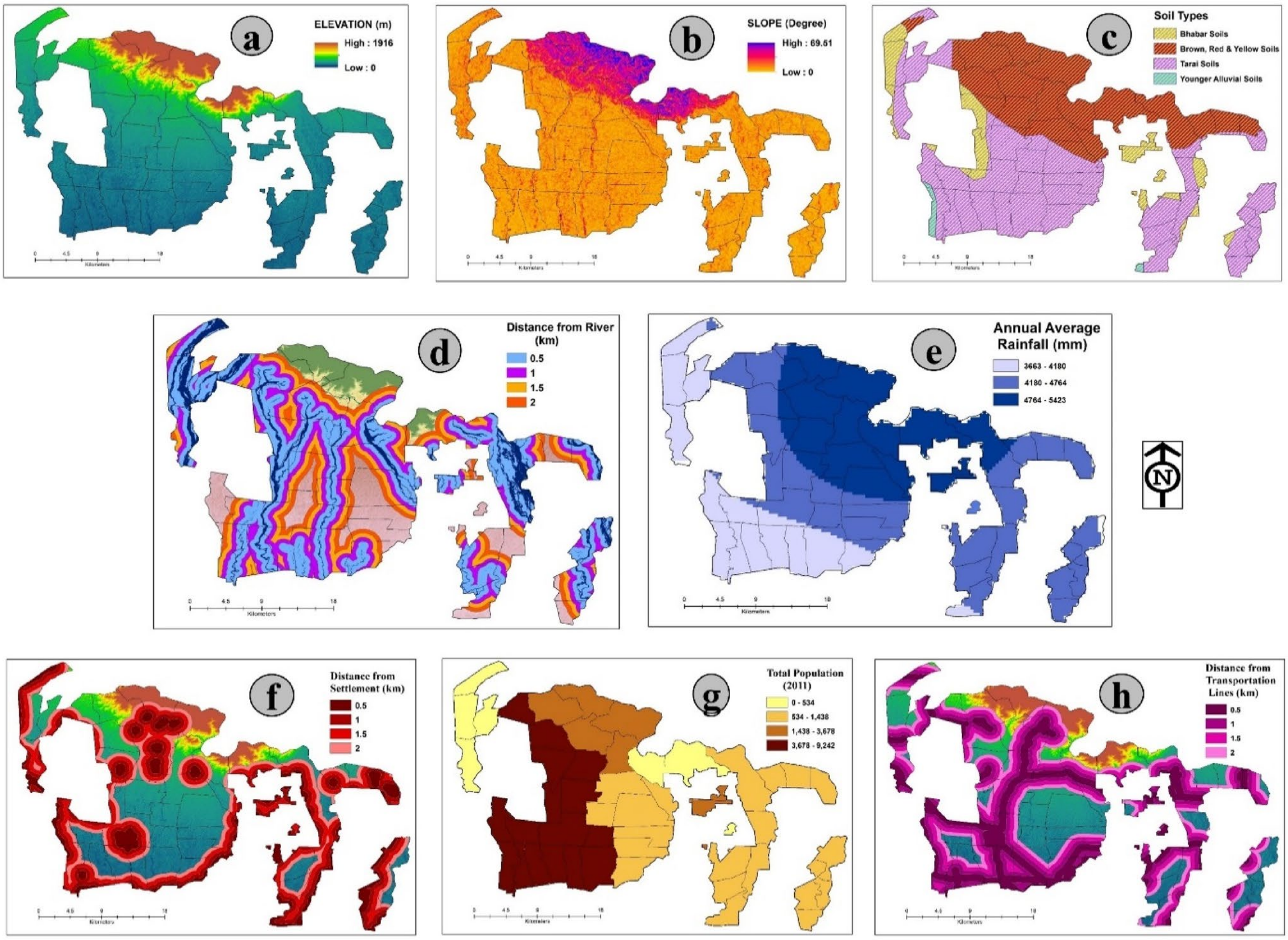

Fig. 4 Different factors of disturbances; under Natural as **a** Elevation, **b** Slope, **c** Soil types, **d** River channels, **e** Rainfall; and Anthropogenic as **f** Settlement site, **g** Total population, **h** Transportation network

$$\mu_{\text{combination}} = \left[\prod_{i=1}^{n}\mu_i\right]^{\gamma}\left[1-\prod_{i=1}^{n}\left(1-\mu_i\right)\right]^{1-\gamma} \quad (5)$$

where γ is a parameter chosen in the range (0,1), and when γ is 1, the combination is equivalent to the fuzzy algebraic product and when γ is 0, it is equivalent to the fuzzy algebraic sum.

The class-wise membership values of vegetation indices are represented in Table 3 to produce a forest health map using fuzzy operators as SUM, PRODUCT, AND, OR, GAMMA (0.5,0.7,0.9).

Analytical Hierarchy Process (AHP)

The analytical hierarchy process (AHP) is a multi-criteria decision-making method based on pair-wise comparison of elements to make a hierarchical structure and develops priorities according to the judgments of the experts or users (Saaty 1980; Saaty 1990; Saaty and Vargas 2000). AHP has followed three basic steps. At first to set the goal or suitability into several criteria and sub-criteria and assign hierarchy according to the relevance of the study. Once it is done, the second step is to judge the relative importance of individual pair of criteria. The importance scale ranges between 1 and 9 where 9 indicates extreme importance and 1 indicates equal importance. Lastly, AHP requires evaluating pair-wise comparison matrices, so that standardized eigenvector extracted from each comparison matrix allows to assign weight to criteria and sub-criteria. The eigenvalue represents the relative ranking of importance of each criterion. In the present study, the eigenvalue of natural and anthropogenic disturbance has been represented in Tables 4 and 5 using Saaty's method (Saaty 1980).

The competence in AHP is estimated by consistency relationship (CR) which is determined using the following Eq. (6).

$$\text{CR} = \frac{\text{CI}}{\text{RI}} \quad (6)$$

where CI means 'Consistency Index' and RI means the 'Random Index'.

Table 3 Distribution of fuzzy membership value of vegetation indices

Forest health indices	Class value	No. of pixel in domain	Percentage of domain	Fuzzy membership value
NDVI	< 0.0	358,626	4.7	0
	0.0–0.242	946,162	12.4	0.2
	0.242–0.317	1,529,119	20.04	0.43
	0.317–0.5	2,099,868	27.52	0.85
	0.5–0.802	2,696,560	35.34	1
SAVI	-0.377–0.10	869,858	11.4	0
	0.10–0.279	1,930,475	25.3	0.37
	0.279–0.553	2,579,053	33.8	0.69
	0.553–1.202	2,250,949	29.5	1
TVI	0.005–0.254	1,315,470	17.24	0.2
	0.254–0.571	2,301,309	30.16	0.57
	0.571–0.923	4,013,556	52.6	0.93
EVI-2	− 0.335–0.165	808,816	10.6	0.18
	0.165–0.289	1,785,498	23.4	0.37
	0.289–0.543	2,083,081	27.3	0.59
	0.543–1.76	2,952,940	38.7	0.84
RERVI	< 0.08	450,190	5.9	0.16
	0.08–0.18	1,249,849	16.38	0.41
	0.18–0.26	1,442,896	18.91	0.61
	0.26–0.34	2,336,409	30.62	0.89
	> 0.34	2,150,991	28.19	1
DVI	< 487	254,853	3.34	0.24
	487–1379	1,556,588	20.4	0.53
	1379–2270	2,342,513	30.7	0.64
	> 2270	3,476,381	45.56	0.89
RVI	0–0.56	2,505,039	32.83	0.87
	0.56–1.00	4,240,177	55.57	0.16
	1.00–1.674	885,119	11.6	0
MSAVI	< − 1.20	236,540	3.1	0.17
	− 1.2—0.48	834,759	10.94	0.31
	0.48–0.67	1,411,612	18.5	0.67
	0.67–0.823	2,368,456	31.04	0.86
	> 0.80	2,778,968	36.42	0.92

Table 4 Weight assignment of natural factors based on AHP

Natural factor	Weight	Sub-class	Score
Distance from River (km)	0.38	0.0.5	4
		0.5–1	3
		1–1.5	2
		1.5–2	1
Elevation (m)	0.25	0–500	4
		500–1000	3
		1000–1500	2
		> 1500	1
Slope	0.19	0–20	4
		20–40	3
		40–60	2
		> 60	1
Average rainfall	0.10	3663–4180	1
		4180–4764	2
		4764–5423	3
Soil Type	0.08	Younger alluvial	4
		Bhabar	3
		Tarai	2
		Brown, red, yellow	1

Table 5 Weight assignment of anthropogenic factors based on AHP

Anthropogenic factor	Weight	Sub-class	Score
Distance from Transport network (km)	0.47	0–0.5	4
		0.5–1	3
		1–1.5	2
		1.5–2	1
Distance from settlement (km)	0.38	0–0.5	4
		0.5–1	3
		1–1.5	2
		1.5–2	1
Population	0.16	0–534	1
		534–1438	2
		1438–3678	3
		3678–9242	4

$$\mathrm{CI} = \frac{\gamma_{\max-n}}{n-1}, \tag{7}$$

where λmax is the highest eigenvalue of the computed matrix and 'n' expresses the order of the matrix.

The natural and anthropogenic disturbances maps were prepared using Disturbance Index (DI) as follows;

$$\mathrm{DI} = (W^*_{1i} \times F1 + W^*_{2i} \times F2 + W^*_{3i} \times \ldots n), \tag{8}$$

where W_{si} ($s = 1, 2, 3$) represents the weight of individual factor that has driven from AHP and F1, F2 are the different factors of disturbance.

AUC-ROC curve

Validation is the most important step for choosing and testing a model. There have many statistical methods used for the validation of the model. In this study, the value of Area Under curve (AUC) of Receiver Operating Characteristic (ROC) has been used (Janizadeh et al. 2019; Bui et al. 2019; Pham et al. 2019) and its mathematical expression is:

$$\mathrm{AUC} = \frac{\left(\sum TC + \sum TD\right)}{(A + B)} \tag{9}$$

where TC denotes the number of correctly classified pixels, TD denotes the number of incorrectly classified pixels, A is the total number of deforested or disturbed pixels, B is the total number of forested pixels.

Modeling methodology

The methodology of this study comprises manifold phases as represented in Fig. 5 and briefly described as follows;

Phase I: According to the purpose of this study, remote sensing and other ancillary data were collected and prepared according to the required GIS module. Then, FL model has been executed using different vegetation indices to assess the health of the forest. The model is validated based on GPS points of disturbed areas of BTR.

Phase II: A spatial database of different natural and anthropogenic factors was prepared at this stage and the AHP model has been implemented to find out the spatial level of both type of disturbances.

Phase III: After analyzing the forest health and level of disturbances, the assessment of forest health and beat-wise impacts of disturbance has been evaluated with the help of spatial matrix and correlation statistics.

Results

Spatial variability of forest health

The spatial health of the forest in BTR has been investigated through remotely sensed data of Sentinal-2 and some specific spectral signatures are noticed in the degraded area of the forest. As in Fig. 6, the difference between NIR (band 8) and Red (band 4) is reduced significantly in the disturbed and non-forested area. Henceforth, vegetation indices with connection to different band algorithms are used further for detecting the spatial variability of forest health with the help of the FL model. The forest heath maps of different fuzzy operators (sum, product, and, or, gamma 0.5, 0.7, 0.9) are represented in Fig. 7.

ArcGIS 10 software was used further to classify the individual maps into five forest health zones (FHZs)

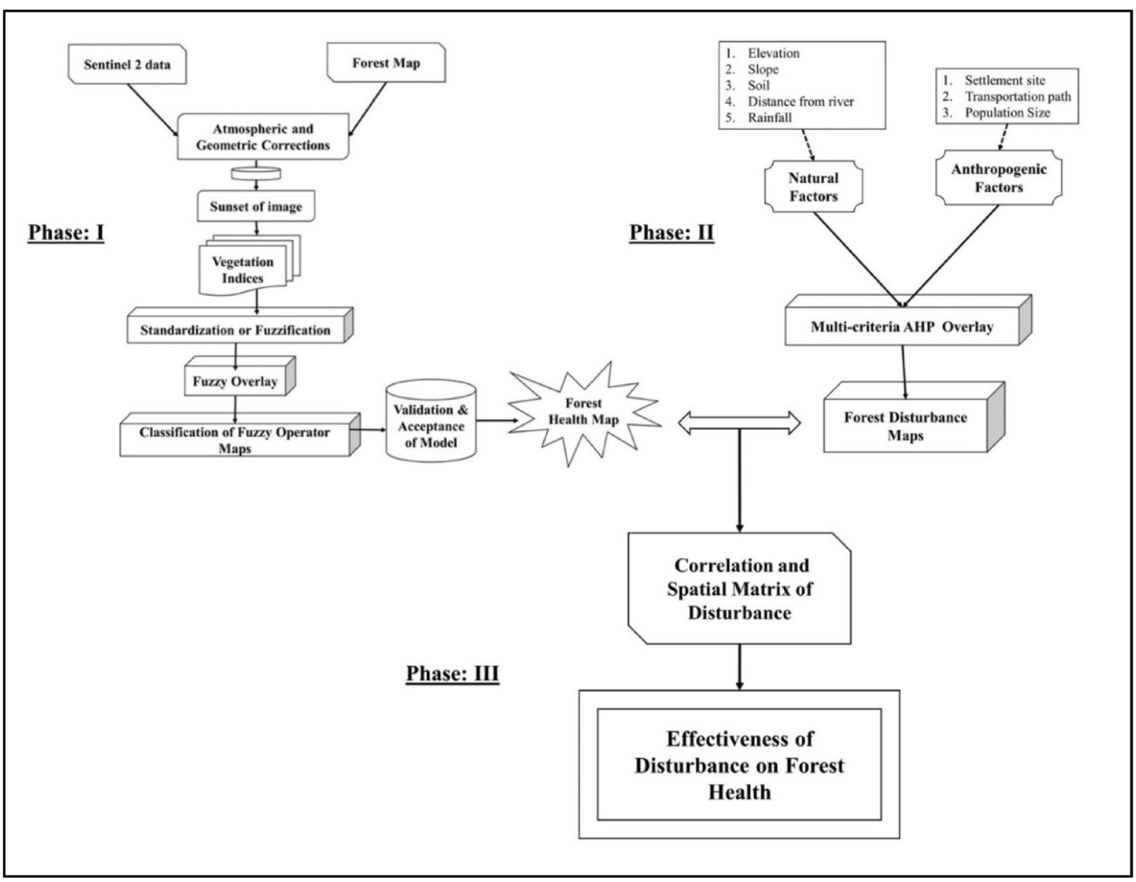

Fig. 5 Detail framework of methodology used in the present study

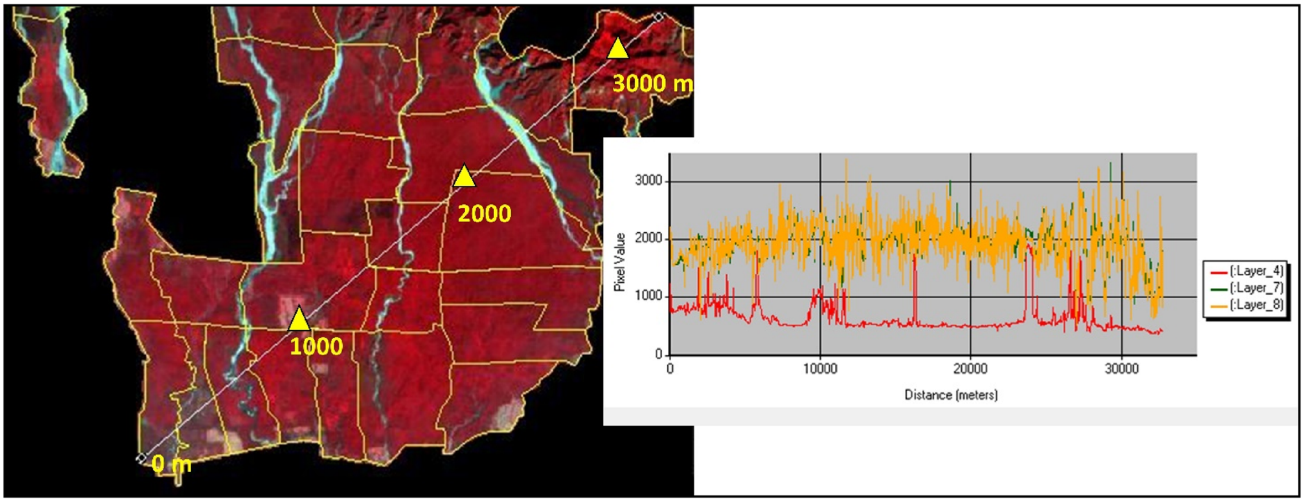

Fig. 6 Spatial profile of some selected bands

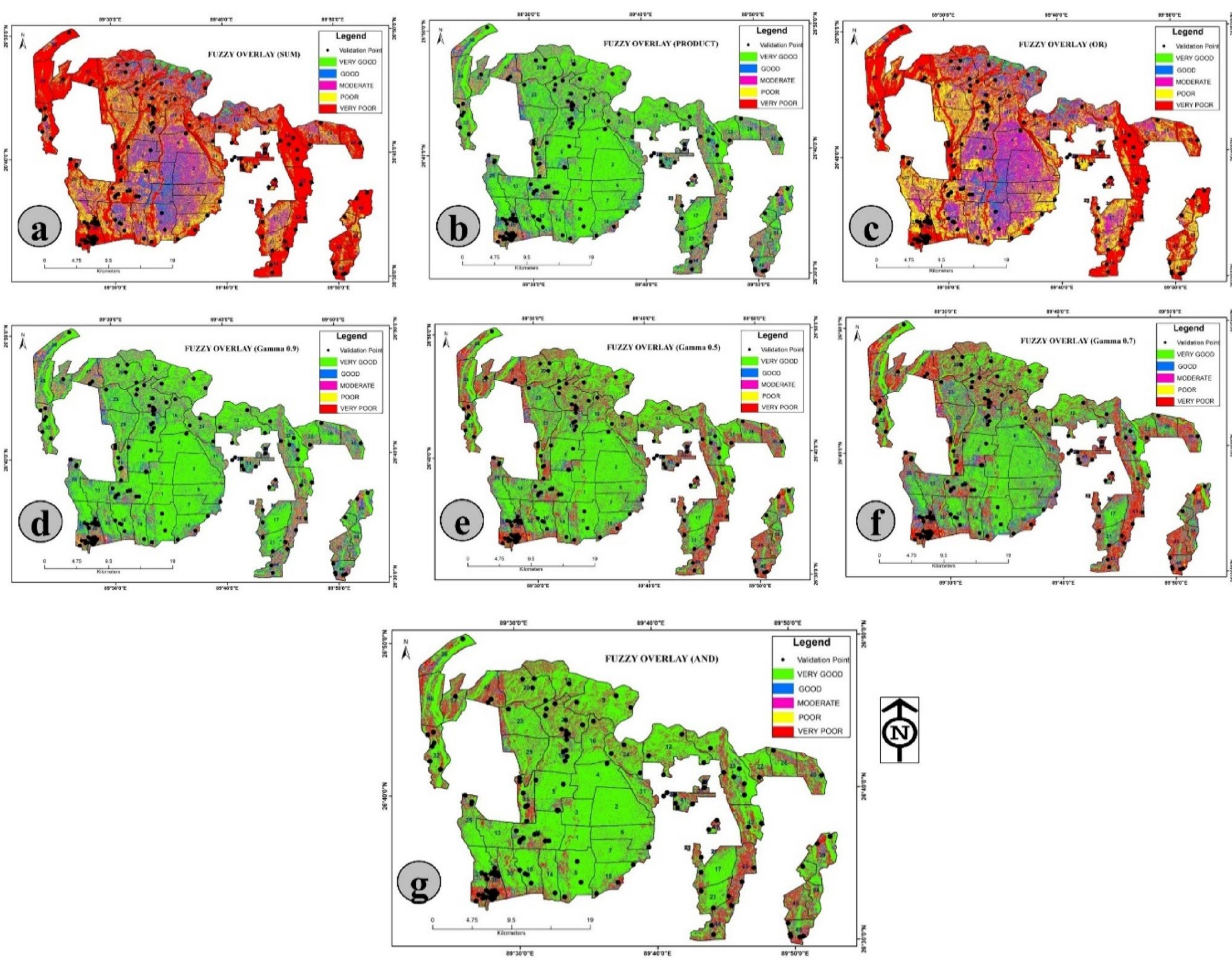

Fig. 7 Forest health maps of BTR based on different fuzzy operators; **a** Sum, **b** Product, **c** Or, **d** Gamma 0.9, **e** Gamma 0.5 **f** Gamma 0.7, **g** And

namely, very good, good, moderate, poor and very poor. The predicted accuracy of FHZs of different fuzzy operators was performed on the basis of ROC curves in this study. A quantitative comparison of the result of different fuzzy operators with success rate are shown in Table 6. The ROC curve is plotted based on model sensitivity (true positive values) versus model specificity (true negative values) on a graph (Deleo 1993; Van Westen et al. 2003). The area under the curve has a value of 1 for perfect prediction and below 0.5 suggests the failure of the model. In comparison to other fuzzy operators, gamma operators clearly produced better result as success rate accuracy is greater than 70% (Fig. 8). The best success accuracy rate of 86.70 is obtained from gamma operator for $\gamma = 0.5$, as it is very likely able to explain its success in predicting the observed disturbed or deforested area of BTR and around 9% and 14% of the area found to be poor to a very poor

Table 6 Success rate of fuzzy operators

Operators	Success rate (%)	Asymptotic significance
Gamma0.5	86.72	0.00
Gamma0.7	73.02	0.01
Gamma0.9	78.71	0.01
Product	38.79	0.19
And	51.90	0.82
Or	50.69	0.94
Sum	42.76	0.39

health condition of the forest. As a result, this gamma operator ($\gamma = 0.5$) has been selected further to judge the effectiveness of natural and anthropogenic disturbances on forest health.

Disturbance regime

The ecosystem of Himalaya mountain is fragile and the fragmentation of forest is evident due to both natural and anthropogenic disturbance (Tiwari 2000; Beniston 2003). Soil erosion, landslide and mass wasting caused by instanced rainfall lead to the flooding situation in the foothills and downstream region. Despite natural degradation, human interferences via encroachment, felling, poaching of trees and withdrawal of boulders, debris are going on within the forest without the approval of the concerned authority. Thus, both types of disturbances are taken under consideration to find out their role and effectiveness of degradation in BTR. The AHP overlay analysis of natural and human footprints reveals that both equally work together to increase the sensitivity of some specific area. The disturbance regime maps show five zones range from very low to very high (Fig. 9). Overall, the imprint of natural disturbance in BTR becomes more (High = 31.58%, very high = 13.78%) in comparison to anthropogenic disturbance (High = 19.07%, very high = 11.09%).

In recent years, remote sensing and GIS in combination with spatial modeling improved our ability to know the spatial structure, pattern and rate of changes across the landscape. This study has executed a spatial matrix (Fig. 10)

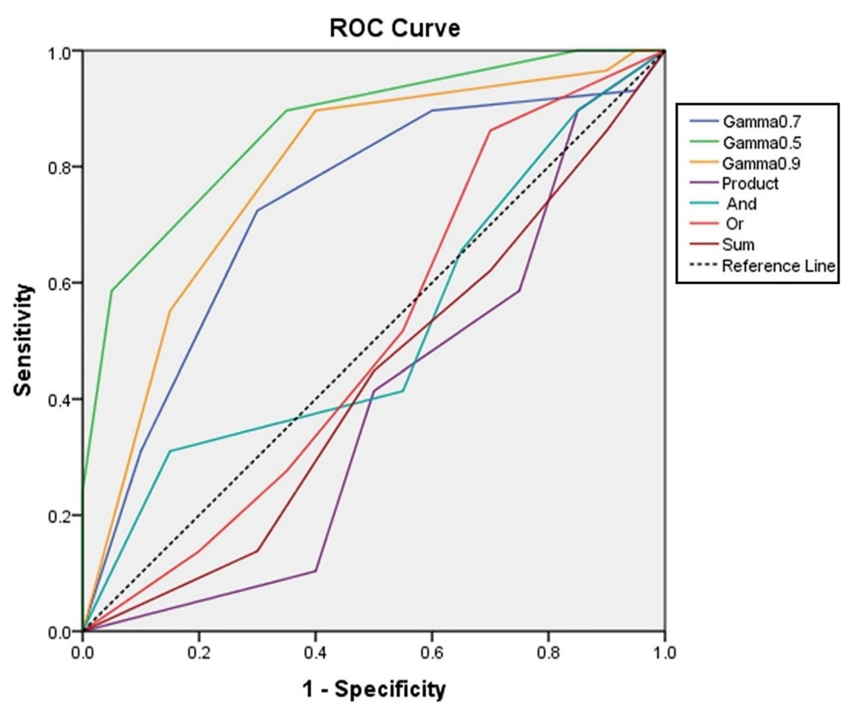

Fig. 8 ROC graph representing curves of different operators

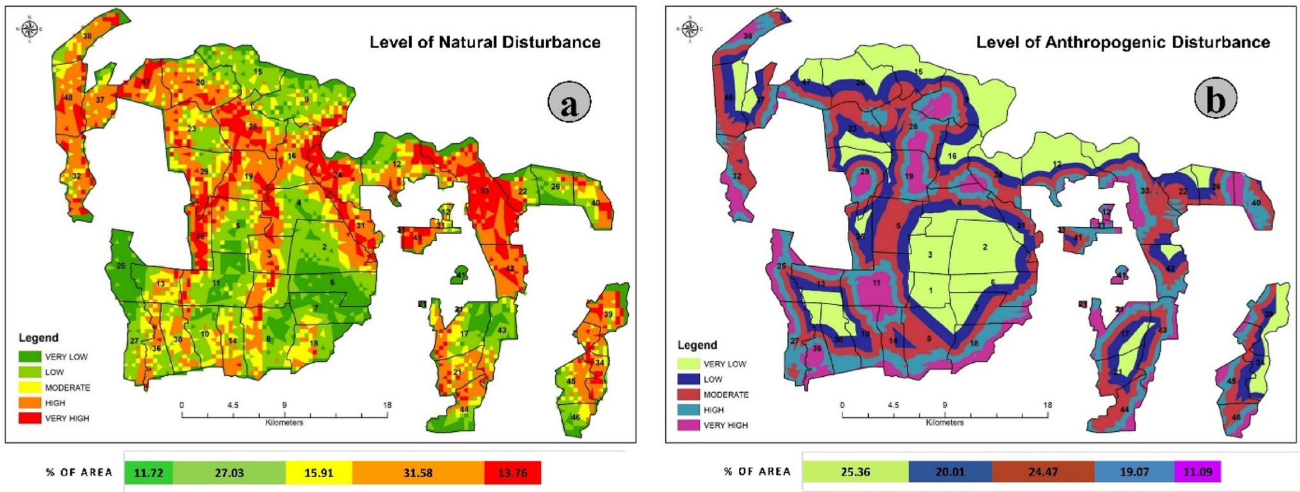

Fig. 9 Spatial variation of level of natural (**a**) and anthropogenic (**b**) disturbances

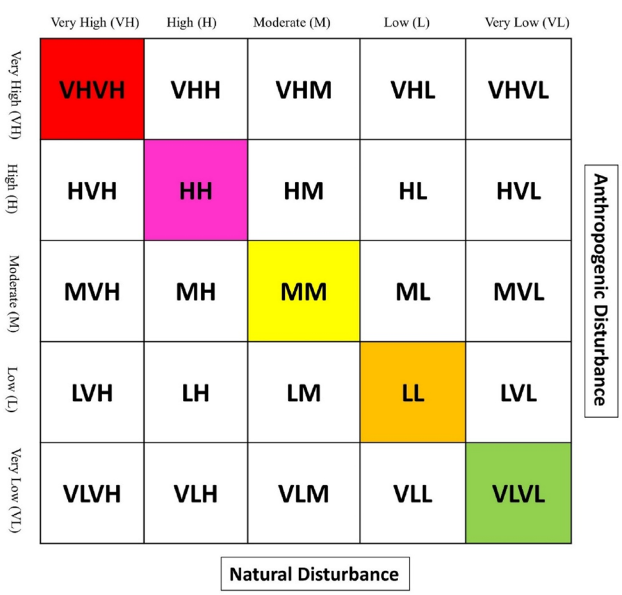

Fig. 10 Spatial matrix of disturbance

with the help of geoprocessing tool like intersection and attributes selection in the GIS environment. The maps of a spatial matrix (Fig. 11) gives us a glimpse of spatial interaction between natural and anthropogenic disturbances in the BTR area at a different level. Moreover, the analysis can further help to find out hotspots of disturbances located at different beats of a forest.

Effect of disturbances on forest health

A theoretical principle used as the framework to judge the real effect of disturbances on forest health is illustrated in Fig. 12. The spatial relationship between heath and disturbances has established through correlation statistics. If there is a negative correlation, i.e., increase of disturbance causes degradation of the forest health or vice versa, then disturbances are effective (with effect) towards deforestation. But when they are positively correlated with the disturbance, then it becomes effectless (without effect) because disturbances do not have a significant impact to destroy the forest health (Fig. 12). So, here the question of other hidden factors like illegal felling with other deforestation activity has come to investigate the real facts thoroughly. In this study, three types of effective relation were found under categories 1, 2 and 4. Category 3 did not persist in any beats of BTR, where disturbance is high but the health of the forest cover is very good. The important beats (ID: 2, 4, 6, 7) which cover the national park area of BTR has noticed to observe a significant negative correlation between forest health and disturbance under the category 2. Those areas are basically experiencing less natural and anthropogenic disturbances with healthy and dense forest cover (Fig. 13). On the other hand, buxa hilly areas of buxa-road and chunabhati beats (ID: 9, 15) show positive effectless disturbances under category 4 because the level disturbance is low but the heath of the forest is not so good. This kind of relationship injects to think critically about the findings of the research. In the case of beats 34 and 37, significant effectless anthropogenic disturbance has been observed but natural distances are significantly effective there (Fig. 13). Moreover, most of the beats in BTR belong to category 1 where high natural and anthropogenic disturbances are responsible to deteriorate the forest health effectively.

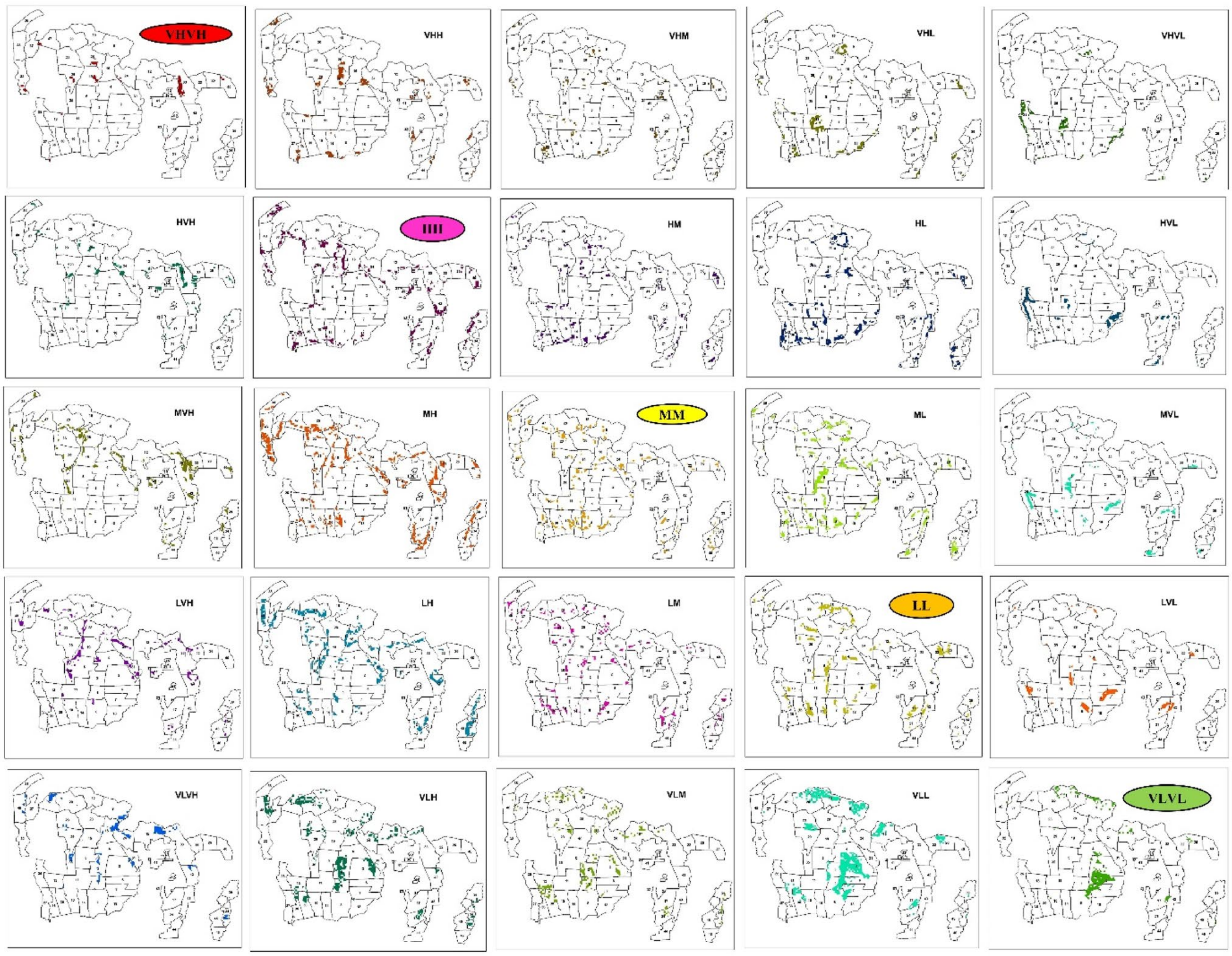

Fig. 11 Outcome of spatial matrix shows site-specific disturbance at different levels

Discussion

Almost every landscape has experienced various disturbances at a different level. It further encourages to cause fragmentation of natural habitat and degradation of the ecosystem. The BTR is valued for its biodiversity and richness, but disturbances make it difficult for wildlife like Bengal Tiger to access their habitat. There has very limited study attempted by the researcher to establish the relationship between disturbance and forest health. The present research is addressed both with consideration of certain factors of disturbance and their effective impacts on some specific places. The location-specific hidden factors are also present in some of the beats (Fig. 14) around buxa hilly area across the border in Bhutan due to the mining activity and felling of trees. The dolomite mining inside the reserve resulting deforestation and soil erosion in upper catchments (Karlsson 2013). The unorganized tree felling is happening in some areas within the reserve forest sometimes which cannot be matched with the footprint or imprint of the factors of disturbance. This study has actually found those conceal areas of BTR under category 4 (Figs 12 and 13) where hidden factors cause forest degradation. As this region is sensitive towards soil erosion, unorganized forest cutting can also disrupt the river course and create a devastating effect on biodiversity. Therefore, regular monitoring of forest cover and integrated planning with watershed management can restore the stability of BTR.

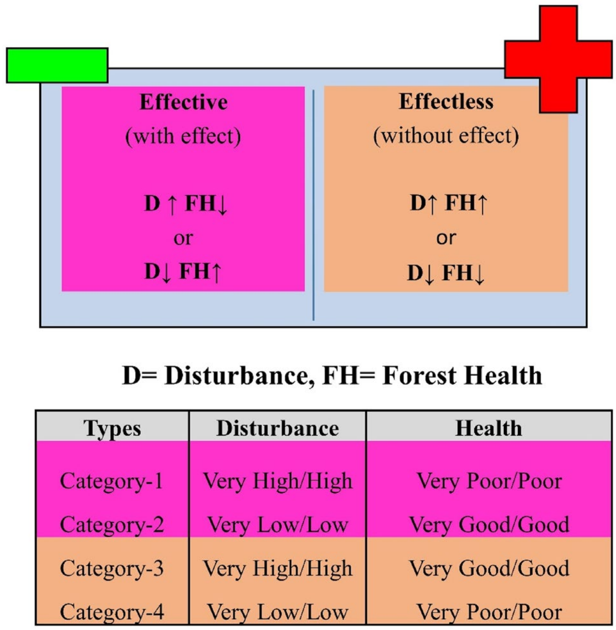

Fig. 12 Workflow to study the effect of disturbance on forest health

geospatial technology helps to find out the distinctiveness of disturbances as associated with associability, connectivity and proximity of some selected variables. Most of the beats in BTR has experienced a different level of natural and anthropogenic disturbances except those beats which cover the core area. Moreover, the assessment of the association between forest health and disturbances guides us to find out the hidden factors like grazing, mining, poaching activities that took place silently within the forest. This kind of monitoring assessment may help further to the planner and policymakers for making strategies and implement an effective forest management scheme in future. Forest is not a static landscape; imposing one model in one area with some set of conditions may not work for other areas, and that is why we found some hidden fragmentation and disturbances. What is important is that an amendment of existing forest policy; regulations need to apply in a particular context and need not be universalized, because the situation in every area is different from others. Especially, the degraded or unstable area must be notified with special care and management strategy.

Conclusion

This paper investigated the nature and level of disturbances on forest heath of BTR using an integrated approach. The

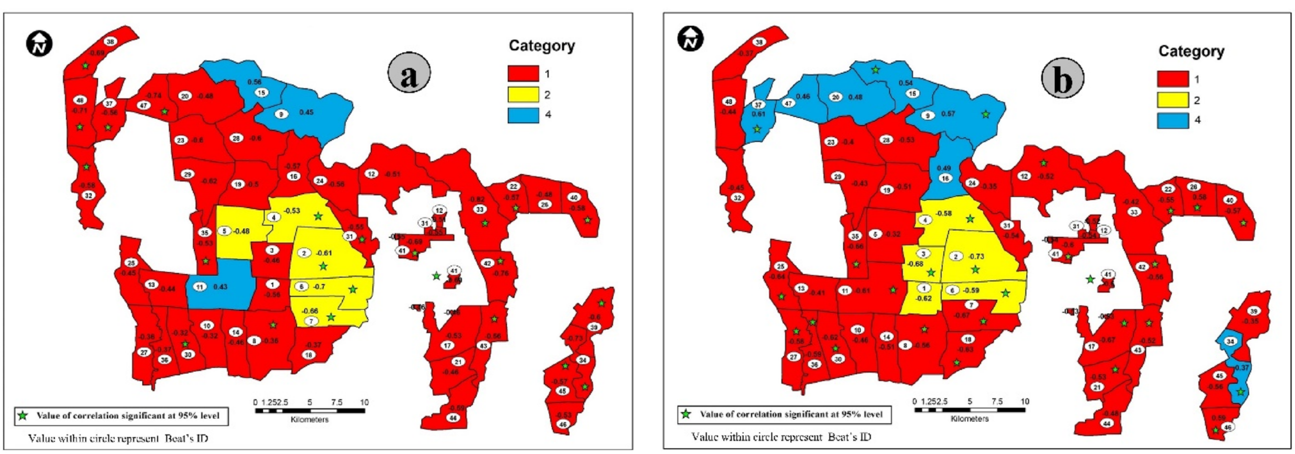

Fig. 13 Maps of correlation represent the relation of forest health with natural (**a**), anthropogenic (**b**) disturbance

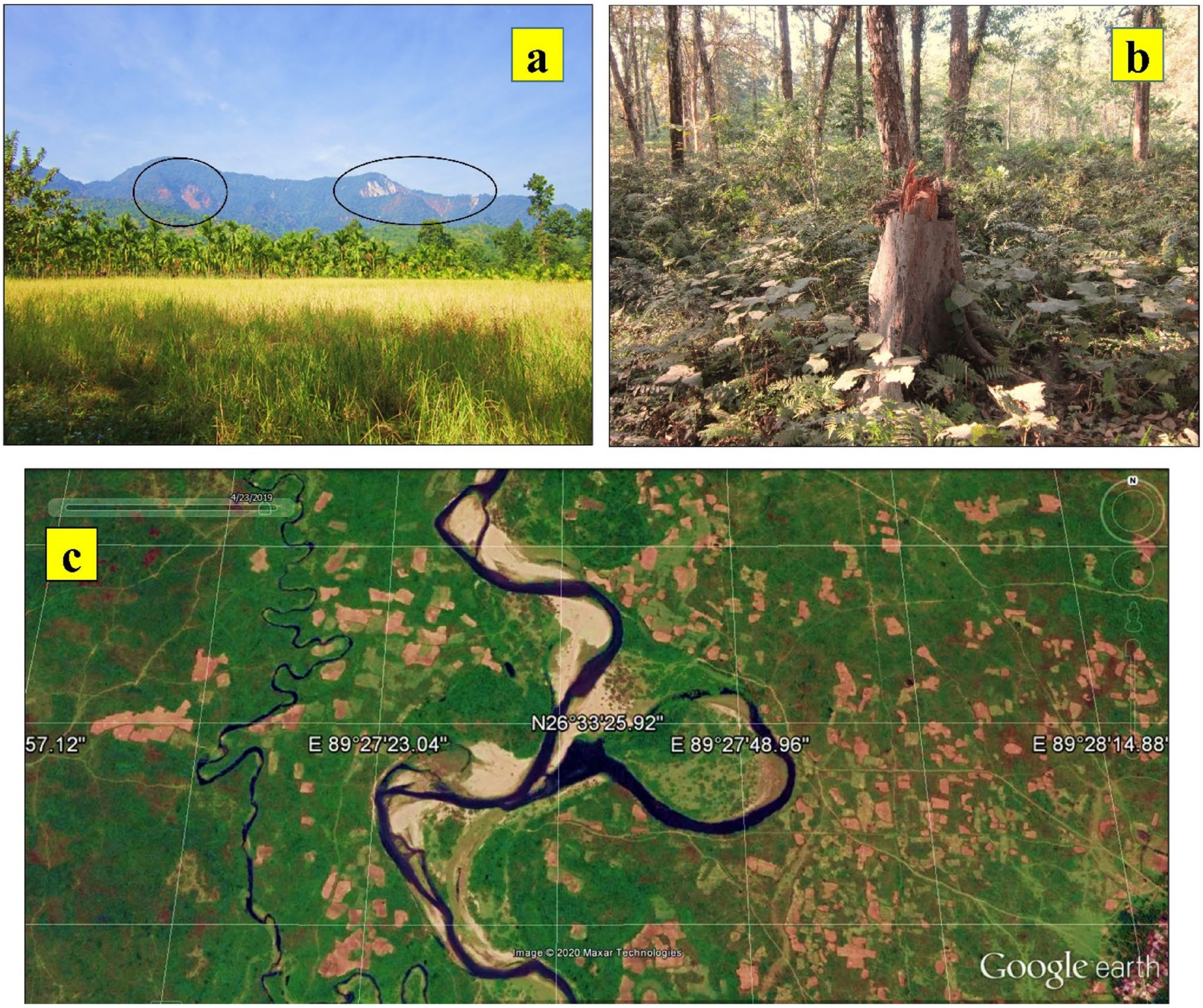

Fig. 14 Selective views of some degraded sites within BTR **a** Mining site in Buxa hills, **b** Felling of trees near new land basti and **c** Patches of deforestation at beat number 27 and 36

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