



Assessing forest health using remote sensing-based indicators and fuzzy analytic hierarchy process in Valmiki Tiger Reserve, India

Roshani¹ · H. Sajjad¹ · M. H. Rahaman¹ · S. Rehman² · M. Masroor¹ · R. Ahmed³

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Abstract

Anthropogenic activities, climate variability and environmental stresses have greatly affected forest ecosystems globally. Thus, monitoring of forest health is essential for proper planning and effective management. The present study employed an integrated approach of remote sensing and fuzzy analytic hierarchy process to assess the forest health in the Valmiki Tiger Reserve in India. Advanced vegetation index, normalized difference vegetation index, normalized difference moisture index, forest fragmentation, rainfall and soil types were derived from remote sensing data. Multiple buffer zones of villages, roads, railways and canals were also determined for analyzing the forest health status. These layers were prepared in the geographical information system. These layers were given weightage using fuzzy analytic hierarchy process. These layers were integrated to prepare forest health map using weighted overlay method. The results revealed that the largest forest area was found under moderately healthy forest (37%) followed by healthy forest (31%) and unhealthy forest (13%). Of the total area of the Reserve, 19% area was under non-forest category. Human-induced disturbances such as encroachment, illegal sand mining, livestock grazing and forest conversion to agriculture have been attributed to the unhealthy forest in the Reserve. The receiver operating characteristic curve value and area under curve (0.792) show reliability of forest health map. The findings of this study may be helpful for forest managers, conservationists and local communities in devising sustainable strategies for effective management of the forest. The methodological framework adopted in this study may be utilized in other geographical regions interested in assessing forest health.

Keywords Forest disturbance · Forest management · Geospatial techniques · Protected area · Site-specific factors

Introduction

Forests play a dynamic role in regulating the climate, supporting the ecological functions and maintaining the environmental balance. These offer essential ecological services and help in the processes of carbon sequestration and nutrient cycle. Forests provide habitat for species and purify air and water (WWF 2021). Forests are being destroyed at an

unprecedented rate, despite of their ecological significance. Over the past few decades, forest cover has declined significantly due to human intervention globally (FAO 2021). Urbanization, industrialization, illegal mining, overharvesting, habitat degradation and other unsustainable management practices have caused forest disturbance across the world (FAO 2010). Degradation and deforestation pose risk for livelihood of the local communities and also intensify climate change to a greater extent (WWF 2021). Climate change, anthropogenic activities, increased frequency of forest fire, occurrence of diseases and long-term changes in succession make the forest ecosystem vulnerable to destruction and unhealthy condition (Sugden et al. 2015). When these disturbances exceed their typical range of fluctuation, extreme consequences can be observed for the forest ecosystems (Moore and Allard 2011). Further, human activities affect forest ecosystems, diversity and forest health resilience (Lausch et al. 2018).

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✉ H. Sajjad
haroon.geog@gmail.com

¹ Department of Geography, Faculty of Natural Sciences, Jamia Millia Islamia, New Delhi, India

² Department of Civil Engineering, National Institute of Technology, Mangalore, Karnataka, India

³ Department of Geography, Nowgong College (Autonomous), Nagaon, Assam, India



Forest health is defined as “a condition that sustains the structure, composition, processes, function, productivity and resilience of forest ecosystems over time and space” (NASEM 2019). A healthy forest is ecologically functional and resistant to disturbances and, therefore, valued by the local communities. The reasons for the adverse forest health and its vitality consequences differ from one area to another. It is not easy to determine the extent and duration of the effects. Overexploitation of forest resources, forest fires, insects and diseases, poor management, inadequate harvesting practices, invasive species, uncontrolled grazing, air pollution and extreme climatic events have been identified as the influencing factors for forest health (Green Facts 2022). It is challenging to unravel the intricacy and interrelationship among these factors and their influence on forest health. Indirect consequences can be widely reached through social, environmental and economic factors (Green Facts 2021). Thus, the identification of suitable factors is imperative for forest health analysis and sustainable management of forest ecosystems (Jain et al. 2020).

Forest health assessment is becoming increasingly important to determine adequate measures for sustainable forest ecosystems (Meng et al. 2019). Healthy forests are more stable and robust to different stresses, disturbances and constraints of resources. With the advancement in technology, remote sensing, geographic information system (GIS) and global positioning system (GPS) have become effective tools for monitoring and determining forest health (Bera et al. 2020; Roshani et al. 2022). Federal and state authorities worldwide are working in collaboration to promulgate programs for monitoring and reporting on the condition of forest ecosystem health (Lausch et al. 2016). Several studies have been conducted to assess forest health at different scales using different methodologies and approaches. Rogers et al. (2008) utilized forest inventory/forest health monitoring programs to detect forest and tree characteristics of the Eastern Arc Mountains of Kenya and Tanzania during 2001–2006. Wulff et al. (2012) reviewed the forest health assessment system of the Swedish forest. They signify local and regional inventories and integrated initiatives to monitor the ecological processes and to provide a broader understanding and better management for forest health. Previous studies have also utilized forest fragmentation and canopy density models for examining the health of the forest (Dutta et al. 2017; Jain et al. 2016; Rahman et al. 2016; Sahana et al. 2015). Czapski et al. (2015) analyzed forest health status using multispectral images acquired by unmanned aerial vehicles (UAV) and verified it using Landsat OLI image. Lyver et al. (2017), based on the perception of the indigenous community 'Maori' of New Zealand, identified indicators and metrics to assess forest health. Lausch et al. (2016, 2018) emphasized on spectral traits to monitor stress, disturbance level, driving factors, limitations, vegetation health

and adaptation mechanisms using remote sensing data. Kayet et al. (2019) utilized hyperspectral and multispectral satellite imagery for assessing forest health of hilltop mining area of *Kiriburu and Meghahatuburu* mines (Jharkhand) and validated the result with field data. Ray et al. (2021) analyzed forest disturbance of the Midnapore subdivision of West Bengal using forest disturbance index and forest fragmentation approach. Nurhaliza et al. (2021) assessed area, health and water quality changes in the mangrove forest of Bali province using normalized difference vegetation index (NDVI) and total suspended solid (TSS) indicators. Multi-criteria decision analysis (MCDA) approaches such as AHP, ANP and FAHP have been widely used for analyzing forest health dynamics (Albulescu and Larion 2019; Dutta et al. 2021; Kayet et al. 2020; Kumar et al. 2021; Mafi-Gholami et al. 2015; Martín-Fernández et al. 2018; Masroor et al. 2022; Limaie and Mohammadi 2018).

Abiotic and biotic disturbances have a great influence on global forest health which have caused massive environmental and economic losses (FAO 2021). Around 40 percent of the world's forest has already been lost by human-induced effects (WWF 2020). Most of the forests in developed nations are already fragmented, and the tendency of developing countries is growing alarmingly (WWF 2021). Fragmentation of forests is recognized as a severe threat to forest health and has become a priority area of research in terrestrial ecosystems (Talukdar et al. 2020). Anthropogenic disturbances including forest clearing, logging, livestock farming and developmental activities in the forests such as unplanned built-ups, irrigation, roads, railways and canals into intact forests lead to forest fragmentation with far-reaching impacts (Uppgupta and Singh 2017). Over recent years, monitoring of forest health conditions has become significant, particularly since the climate and other stressors have adversely affected forests globally (Barka et al. 2018).

Forests of mountain ecosystems are more vulnerable to global warming in response to increased land degradation and overexploitation of resources. Vegetation phenological changes and declining forest cover have brought numerous environmental concerns in the Himalayan region (Sharma et al. 2021). The protected areas of terai-arc landscape (low land area) are mainly spread over three states of India namely Uttarakhand, Uttar Pradesh and Bihar. Valmiki Tiger Reserve (VTR) located in terai arc landscape runs parallel to the foothills of the Himalayas. The terai landscape (low land region) is one of the most fragmented and threatened ecosystems in Asia (Wikramanayake et al. 2010). Nearly 70% of this landscape is directly used by humans for agriculture and settlement. Over the last two decades, high population growth, agricultural expansion and changing socio-economic objectives are the critical challenges for forest management in this landscape (Semwal 2005). VTR has been subjected to more anthropogenic stressors including



overharvesting, overgrazing, illegal logging and sand mining. Poverty is rampant in VTR, and therefore, indigenous communities are highly dependent on forest for domestic and commercial use. Few studies have employed fuzzy analytic hierarchy process (FAHP) for assessing forest health status at local level. Further, a small number of studies has been attempted to analyze the association between disturbances and forest health. Thus, the present study makes an attempt to assess forest health conditions in Valmiki Tiger Reserve using GIS-based FAHP model. The main objectives of the study were as follows: (1) to identify the remote sensing data derived factors based on literature survey, (2) to assign weights to the influencing factors based on their relative importance through fuzzy analytic hierarchal process, (3) to integrate all the factors using weighted overlay analysis to prepare forest health map and 4) to analyze the relationship between influencing factors and forest health. The study was conducted in Valmiki Tiger Reserve using remote sensing data during 2016–2020, rainfall gridded data from 2011 to 2020, soil types data of 1972 and attribute data of village locations, roads, railways and canals of the year 2021.

Materials and methods

Study area

Valmiki Tiger Reserve (VTR) lying in the West Champaran district of Bihar state in India forms the eastern limit of the Himalayan *Terai* (low land region) forests and adjoins the international border of Nepal. The study area is located between 27° 10' and 27° 30' North latitudes and 83° 50'–84° 10' East longitudes (Fig. 1). This Reserve is contiguous with Nepal's Chitwan National Park in the north and Sohagibarwa Wildlife Sanctuary of Uttar Pradesh in the west. The total geographical area of the tiger reserve is 901.13 km². The tiger reserve encompasses the foothills of the Himalayan Shivaliks and contains pristine forest. It is comprised of Valmiki National Park and Valmiki Wildlife Sanctuary. The Reserve is divided into two forest divisions and eight ranges. Division 1 contains *Gobardhana*, *Manguraha* and *Raghia* ranges. Division 2 covers *Chiutaha*, *Gonauli*, *Harnatanar*, *Madanpur* and *Valmiki Nagar*. The Reserve was constituted as the 18th Tiger Reserve of India (Government of Bihar 2018).

The VTR is situated in the bio-geographic zone of the Gangetic plains of the country. Its terrain is drained by various rivers and streams. The elevation of the Reserve ranges between 140 and 874 m above mean sea level. Highly rugged terrain and steeper slope are found in the western part of the Reserve (Maurya and Borah 2013). The Reserve experiences three clearly defined seasons namely summer, winter

and monsoon. The maximum temperature exceeds 43 °C while the minimum temperature drops to 5 °C. Annual precipitation in the Reserve is 1106 mm. Most of the rainfall is received through southwest monsoon (Kumar and Sinha 2016).

VTR has a unique blend of *terai-bhabar* flora and fauna. The main forest types in the Reserve include tropical semi-evergreen forest, tropical moist deciduous forest, littoral and swamp forest, tropical dry deciduous forest and plantation (ISFR 2021). Other vegetation comprises *bhabar dun sal*, *dry siwalik sal*, *khair-sissoo* forest, cane brakes, eastern wet alluvial grassland, western Gangetic moist mixed deciduous forest and barringtonia swamp forest (Champion and Seth 1968). *Shorea Miliusa robusta*, *Terminalia belerica*, *velutina*, *Adina cordifolia*, *Terminalia Tomentosa*, *Lagerstroemia parviflora*, *Trewia nudiflora*, *Acacia catechu* *Salmalia malabarica* and *Mallotus philippensis* are the major tree species of the Reserve. The VTR landscape consists of very dense forest (30%), moderately dense forest (61%), open forest (8%) and scrub (1%) (ISFR 2021). The diverse of physiography, geology and climate make mosaic of vegetation and faunal habitats and form niches for various species of plants and animals (Chanchani et al. 2014). The southern periphery of the Reserve consists of human habitats and agricultural fields. The main economic activity in the Reserve is agriculture. However, the people are also dependent on forest products for their sustenance.

Selection of thematic layers

Forest health analysis is an effective tool for the conservation and management of forest resources. The study utilized satellite and ancillary data for preparing layers of influencing factors. Forest health is influenced by a number of factors directly and indirectly. Based on the literature survey, ten influencing factors were selected. Six direct and four indirect factors were selected for analyzing forest health in the VTR. Direct factors influencing forest health dynamics of VTR included advanced vegetation index (AVI), normalized difference vegetation index (NDVI), normalized difference moisture index (NDMI), forest fragmentation, rainfall and soil type, whereas indirect factors included distance from villages, roads, railways and canals.

The base map of Valmiki Tiger Reserve was obtained from the Environment and Forest department, Bettiah (West Champaran). AVI, NDVI and NDMI were derived using Landsat 8 OLI. The median values of each index were considered from 2016 to 2020 to remove the biasness. The thematic layers of AVI, NDVI and NDMI were prepared in the google earth engine (GEE) using the following equations:



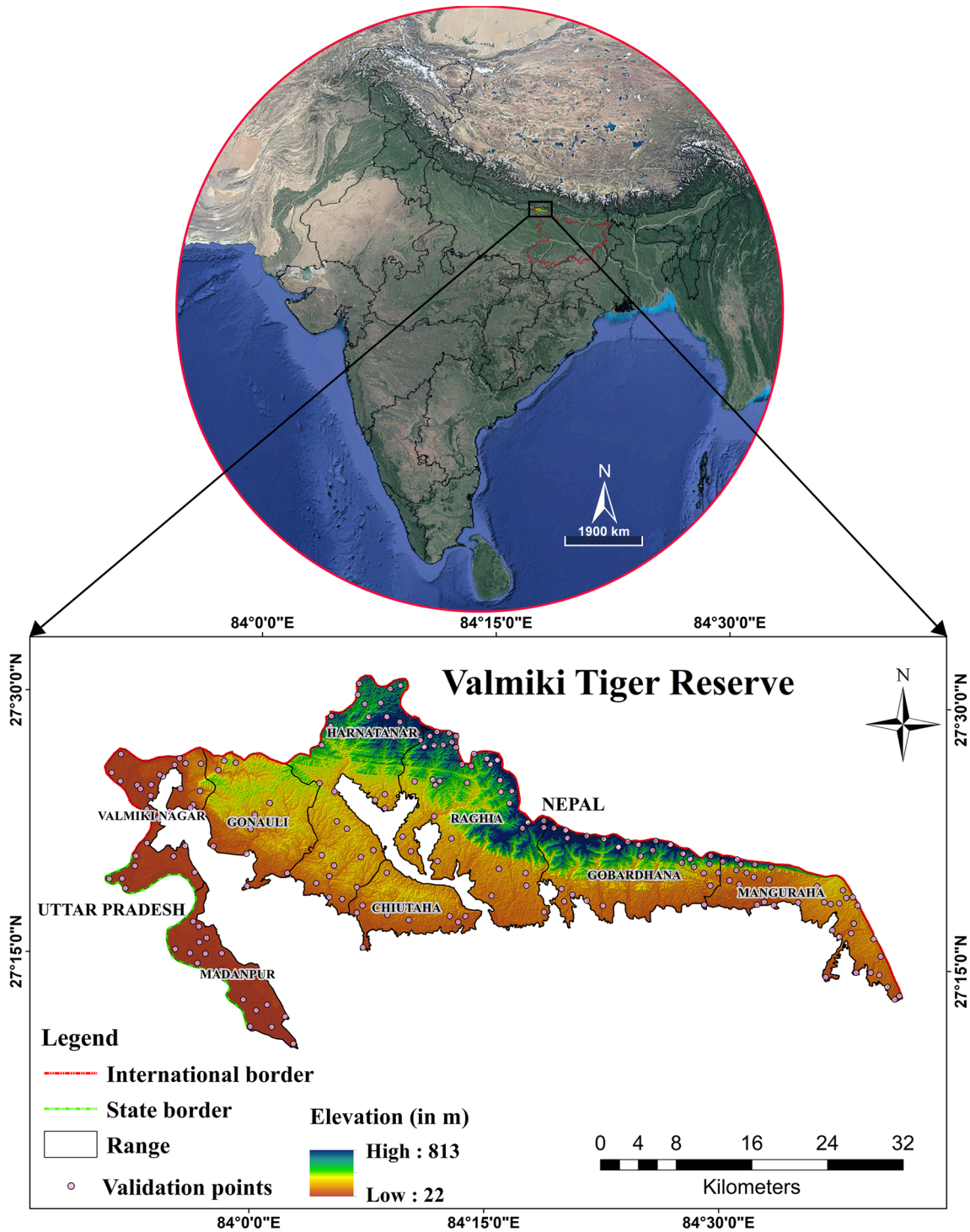


Fig. 1 Location map of the study area

$$AVI = [NIR * (1 - RED) * (NIR - RED)]^{1/3} \quad (1)$$

$$NDVI = (NIR - RED) / (NIR + RED) \quad (2)$$

$$NDMI = (NIR - SWIR) / (NIR + SWIR). \quad (3)$$

The forest fragmentation map was prepared using Sentinel-2A satellite data and the landscape fragmentation tools (LFT v2.0) following Devi et al. (2021). The rainfall

map was prepared using Indian meteorological department (IMD) (2011–2020). The soil type map for the present study was acquired from the Food and Agricultural Organization (FAO). The road map of VTR was obtained from open street map (OSM). Location of villages, railway lines and canals were extracted from Google Earth Pro. Further, multiple buffer rings were created to determine their level of disturbance on forest health. The details and sources of the thematic layers used for examining the health of the forest are present in Table 1. The steps for the methodological framework adopted in the study are shown in Fig. 2.

Calculation of normalized weights using fuzzy AHP method

AHP is widely utilized in recent studies of land-use planning, groundwater and forest assessments for its efficacy and management traits (Saaty 1980). In order to increase the accuracy of hierarchical analysis, van Laarhoven and Pedrycz (1983) modified the conventional AHP approach in 1983 by employing fuzzy ratios rather than exact ratios (Rahaman et al. 2022). FAHP provides crisp values and does not reduce personal judgment vagueness (Ahmed et al. 2018). Several researchers have explored the effectiveness of FAHP in handling the vagueness, uncertainty and fuzziness associated with decision-making process and mapping (Ahmed et al. 2018; Jain et al. 2021; Mafi-Gholami et al. 2015). In the present study, fuzzy AHP was utilized for applying multi-criteria decisions and preparing forest health map. A triangular fuzzy comparison matrix was prepared to determine the priority vector. The

preference of one vector over the other was decided using a linguistic scale (Table 2). Finally, fuzzy weights were assigned to rank based on their importance (Table 3). Forest health map was then prepared using weighted overlay method.

Comparison matrix of triangular fuzzy scale was determined to obtain significant forest health classes through FAHP (F). FAHP (F) was obtained as:

$$F_{1gi}, F_{2gi}, F_{3gi}, F_{4gi}, F_{ngi}$$

where g_i is the goal set for criterion, and F_{1gi} are triangular fuzzy numbers. Step-wise processor of FAHP by Ahmed et al. (2018) was followed for Fuzziness for the i th criterion (M_1) is expressed as

$$M_1 = \sum_{j=1}^m F_{jgi} \times \left[\sum_{i=1}^n \sum_{j=1}^m \widetilde{M}_{jgi} \right]^{-1} \tag{4}$$

It can be computed as:

$$\sum_{j=1}^m F_{jgi} \tag{5}$$

A new set of fuzzy values for x (lower limit), y (middle limit) and z (upper limit) was obtained using Eq. 6:

$$\sum_{j=1}^m F_{jgi} = \left[\sum_{j=1}^m x_j, \sum_{j=1}^m y_j, \sum_{j=1}^m z_j \right] \tag{6}$$

From the set of x, y and z , Eq. (7) was obtained:

Table 1 Thematic layers and their sources

| Thematic Layer | Source | Time period |
|----------------------|---|------------------------------|
| AVI | Prepared using satellite imageries (LANDSAT 8 OLI) in google earth engine (GEE) https://code.earthengine.google.com/ | Median values from 2016–2020 |
| NDVI | Prepared using satellite imageries (LANDSAT 8 OLI) in google earth engine (GEE) https://code.earthengine.google.com/ | Median values from 2016–2020 |
| NDMI | Prepared using satellite imageries (LANDSAT 8 OLI) in google earth engine (GEE) https://code.earthengine.google.com/ | Median values from 2016–2020 |
| Forest fragmentation | Prepared utilizing LFT v2.0 using satellite imageries (Sentinel 2-A) from USGS earth explorer https://earthexplorer.usgs.gov/ | November 2019 |
| Rainfall | Indian meteorological department https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html | 2011–2020 |
| Soil type | Food and agriculture organization, United nations http://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/faunesco-soil-map-of-the-world/en/ | 1972 |
| Canal | Digitized from google earth pro | April 2021 |
| Village | Digitized from google earth pro | April 2021 |
| Roads | OpenStreetMap (OSM) https://www.openstreetmap.org/#map=9/27.3024/84.3816&layers=T | 2021 |
| Railways | Digitized from google earth pro | April 2021 |

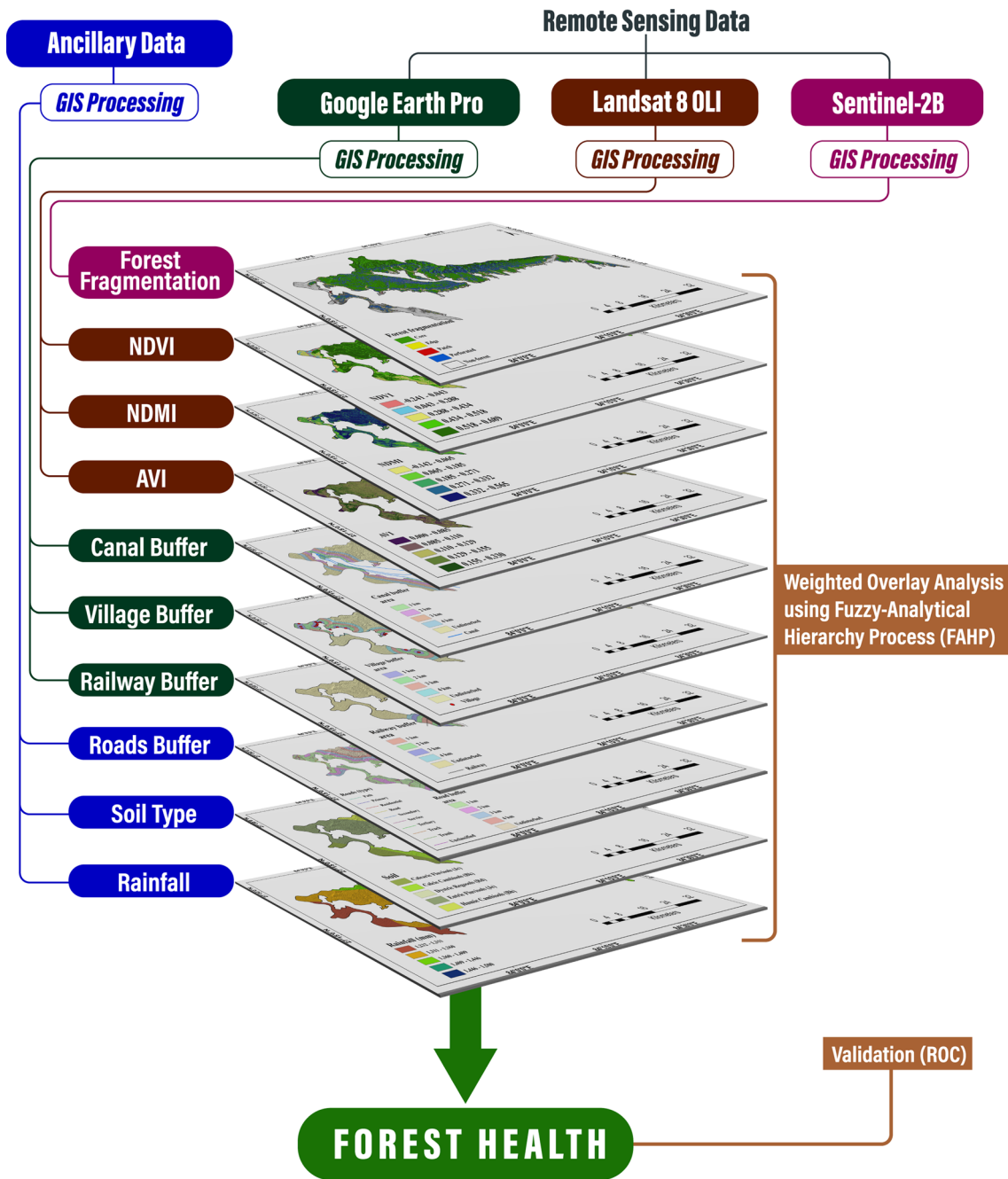


Fig. 2 Methodological framework

$$\left[\sum_{i=1}^n \sum_{j=1}^m F_{jgi} \right]^{-1}$$

The inverse vector for fuzzy values was determined as:

$$\left[\sum_{i=1}^n \sum_{j=1}^m F_{jgi} \right] = \left[\sum_{j=1}^m x_j, \sum_{j=1}^m y_j, \sum_{j=1}^m z_j \right] \tag{8}$$

By inverting vector, Eq. (9) was obtained:

$$\left[\sum_{i=1}^n \sum_{j=1}^m F_{jgi} \right]^{-1} = \left[\frac{1}{\sum_{i=1}^n x_i}, \frac{1}{\sum_{i=1}^n y_i}, \frac{1}{\sum_{i=1}^n z_i} \right] \tag{9}$$

The degree of possibility for $(F_1 \geq F_2)$ is calculated as:

$$V(F_1 \geq F_2) = \sup_{c \geq d} \left[\min \left(\mu_{E_{1(c)}}, \mu_{E_{2(d)}} \right) \right] \tag{10}$$

$VV(F_1 \geq F_2) = 1$, c and d are the membership function.

Table 2 Triangular fuzzy scale (after Lee et al. 2013)

| Linguistic scale | Triangular fuzzy scale | Triangular fuzzy reciprocal scale |
|------------------------------|------------------------|-----------------------------------|
| Absolutely more important | (5/2, 3, 7/2) | (2/7, 1/3, 2/5) |
| Very strongly more important | (2, 5/2, 3) | (1/3, 2/5, 1/2) |
| Strongly more important | (3/2, 2, 5/2) | (2/5, 1/2, 2/3) |
| Weakly more important | (1, 3/2, 2) | (1/2, 2/3, 1) |
| Equally important | (1/2, 1, 3/2) | (2/3, 1, 2) |
| Just equal | (1, 1, 1) | (1, 1, 1) |

Since F_1 and F_2 are convex fuzzy numbers and have:

$$\begin{aligned} V(F_1 \geq F_2) &= \text{if}q_1 \geq q_2 \\ V(F_2 \geq F_1) &= \text{hgt}(F_1 \cap F_2) = \mu_{q_1(e)} \end{aligned} \tag{11}$$

where (e) is the highest intersection point lying between (μ_{F_1}) and (μ_{F_2}) .

The ordination of d for F_1 and F_2 is expressed as:

$$V(F_2 \geq F_1) = \text{hgt}(F_1 \cap F_2) = \frac{(x_1 - z_2)}{(y_2 - z_2) - (y_1 - x_1)} \tag{12}$$

The degree of possibility for convex fuzzy number can be expressed as:

$$\begin{aligned} V(F \geq F_1, F_2, \dots, F_k) \\ &= V[(F \geq F_1) \text{ and } (F \geq F_2) \dots \text{ and } (F \geq F_k)] \\ &= \min V(F \geq F_i); i = 1, 2, 3, \dots, k. \end{aligned} \tag{13}$$

Equation (13) on degree of possibility is supported by:

$$e(R_1) = \min V(M_i \geq M_k)$$

where $k = 1, 2, 3, \dots, n; k \neq i$. The weight vectors are expressed as:

$$S_1 = [e(R_1), e(R_2), e(R_3) \dots, e(R_n)]^T \tag{14}$$

where $S_i (i = 1, 2, 3, \dots, n)$.

Normalization of the weight vectors can be obtained as:

$$S = [e(R_1), e(R_2), e(R_3) \dots, e(R_n)]^T \tag{15}$$

where S represents a non-fuzzy number.

Forest health map

Each thematic layer was processed in a GIS environment and converted into a raster layer for the final overlay. Fuzzy AHP produced weights and rankings are presented in Table 4.

Table 3 Pairwise comparison matrix and weightage of forest health conditioning factors

| | AVI | NDVI | NDMI | Rf | FF | So | V | Rd | Rl | C | W |
|------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|---------------|---------------|---------------|---------------|--------|
| AVI | (1, 1, 1) | (1, 3/2, 2) | (3/2, 2, 5/2) | (2, 5/2, 3) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | 0.2043 |
| NDVI | (1/2, 2/3, 1) | (1, 1, 1) | (1/2, 1, 3/2) | (1, 3/2, 2) | (3/2, 2, 5/2) | (2, 5/2, 3) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | 0.1570 |
| NDMI | (2/5, 1/2, 2/3) | (2/3, 1, 2) | (1, 1, 1) | (1/2, 1, 3/2) | (1, 3/2, 2) | (3/2, 2, 5/2) | (2, 5/2, 3) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | 0.1383 |
| Rf | (1/3, 2/5, 1/2) | (1/2, 2/3, 1) | (2/3, 1, 2) | (1, 1, 1) | (3/2, 2, 5/2) | (3/2, 2, 5/2) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | (2, 5/2, 3) | 0.1353 |
| FF | (2/7, 1/3, 2/5) | (2/5, 1/2, 2/3) | (1/2, 2/3, 1) | (2/5, 1/2, 2/3) | (1, 1, 1) | (1, 3/2, 2) | (1, 3/2, 2) | (3/2, 2, 5/2) | (3/2, 2, 5/2) | (3/2, 2, 5/2) | 0.0873 |
| So | (2/7, 1/3, 2/5) | (1/3, 2/5, 1/2) | (2/5, 1/2, 2/3) | (2/5, 1/2, 2/3) | (1, 1, 1) | (1, 1, 1) | (1, 3/2, 2) | (3/2, 2, 5/2) | (2, 5/2, 3) | (5/2, 3, 7/2) | 0.0820 |
| V | (2/7, 1/3, 2/5) | (2/7, 1/3, 2/5) | (1/3, 2/5, 1/2) | (2/7, 1/3, 2/5) | (1/2, 2/3, 1) | (1, 1, 1) | (1, 1, 1) | (1/2, 1, 3/2) | (1/2, 1, 3/2) | (1, 3/2, 2) | 0.0550 |
| Rd | (2/7, 1/3, 2/5) | (2/7, 1/3, 2/5) | (2/7, 1/3, 2/5) | (2/7, 1/3, 2/5) | (2/5, 1/2, 2/3) | (2/5, 1/2, 2/3) | (2/3, 1, 2) | (1, 1, 1) | (1/2, 1, 3/2) | (1, 3/2, 2) | 0.0513 |
| Rl | (2/7, 1/3, 2/5) | (2/7, 1/3, 2/5) | (2/7, 1/3, 2/5) | (2/7, 1/3, 2/5) | (2/5, 1/2, 2/3) | (1/3, 2/5, 1/2) | (2/3, 1, 2) | (2/3, 1, 2) | (1, 1, 1) | (1, 3/2, 2) | 0.0513 |
| C | (2/7, 1/3, 2/5) | (2/7, 1/3, 2/5) | (2/7, 1/3, 2/5) | (1/3, 2/5, 1/2) | (2/5, 1/2, 2/3) | (2/7, 1/3, 2/5) | (1/2, 2/3, 1) | (1/2, 2/3, 1) | (1/2, 2/3, 1) | (1, 1, 1) | 0.0433 |

*AVI Advance vegetation index, NDVI Normalized difference vegetation index, NDMI Normalized difference moisture index, FF Forest fragmentation, Rf Rainfall, So Soil type, C Canal, V Village, Rd Roads, Rl Railway, W Fuzzy Weight



Jenks natural break classification scheme (Jenks 1967) was used to classify the study area into four categories of forest health namely healthy forest, moderately healthy forest, unhealthy forest and non-forest.

Result validation

The values of area under curve (AUC) of receiver operating characteristics (ROC) have been utilized in the present study. The ROC curve is a beneficial tool for comparing quality and determining probability and prediction (Kayet et al. 2020). AUC values ranging between 0.5 and 0.6 signify poor prediction, 0.6 and 0.7 indicate average prediction, 0.7 and 0.8 show good prediction, 0.8 and 0.9 show very good prediction and 0.9 and 1 indicate excellent prediction (Mukherjee and Singh 2020). The mathematical expression of ROC curve is expressed as:

$$AUC = \frac{(\sum TC + \sum TD)}{(A + B)} \quad (16)$$

where TC denotes number of correctly classified pixels, TD indicates number of incorrectly classified pixels, A denotes total number of unhealthy forest pixels and B denotes total number of healthy forested pixels.

Results and discussion

Results

Forest disturbance is taken as an influential factor affecting forest health. It is generally the spatial distortion in the forest cover caused by spatial effects of different parameters. The factors influencing forest and their relationship, degree of influence and spatial distribution have been discussed in the following sub-sections.

Advanced vegetation index (AVI)

AVI is a numerical indicator to determine healthy vegetation based on the red and near-infrared spectral bands (Bera et al. 2020). It uses spectral reflectance from multispectral image to extract vegetation condition. This index shows forest density and highlights subtle differences in canopy density (Roy et al. 1996). The AVI value ranged from 0 to 0.33 (Fig. 3a). It was further reclassified into five classes as very low (0–0.085), low (0.085–0.110), moderate (0.110–0.129), high (0.129–0.155) and very high (0.155–0.330). The western part of the reserve shows very high AVI values whereas the northern and central part shows high AVI values due to the concentration of dense forest on high elevation. The

southern and eastern parts of VTR showed low and very low AVI values due to the presence of water bodies, sand beds, wetlands, grasslands, shrubs and agricultural fields. The higher values of AVI (0.28–0.56) represented healthy forest and were assigned high rank while lower values (0.00–0.25) represented unhealthy forest to non-forest areas and thus were given low ranks.

Normalized difference vegetation index (NDVI)

NDVI is a vegetation index representing vegetation distribution and indicating appropriate vegetation health conditions of a particular region. Rouse (1974) initially utilized the NDVI index in 1974 to assess vegetation health and growth in a specific area. The values range from +1 to –1. High value implies higher vegetation health, whereas low value indicates poor vegetation health. The NDVI values in VTR ranged from –0.241 to 0.689. It was classified into five categories of very low (–0.241–0.043), low (0.043–0.288), moderate (0.288–0.434), high (0.434–0.518) and very high (0.518–0.689). Figure 3b shows the vegetation condition in VTR. Very low to low values signify unhealthy and non-forest areas and were assigned low rank. The moderate NDVI values were noticed for grasslands and agricultural fields. High to very high values (0.434–0.689) were given higher ranks and represent high canopy vegetation indicating healthy forest. The dense forest is mainly dominated by *Sal* mixed type vegetation lying in the northern and central parts of the core zone of the Reserve.

Normalized difference moisture index (NDMI)

The vegetation structure and moisture content are closely interrelated. Therefore, determining the moisture content is essential for assessing the health of the vegetation. NDMI has frequently been used to monitor forest ecosystem moisture, and consequently, overall forest health (Sankey et al. 2021). NDMI was proposed by Hardisky et al. (1984) and Gao (1996) to measure the biomass and moisture content of vegetation (Zhang et al. 2016). This index has the advantage of being able to identify vegetative structures that have been minimally disturbed (Hladky et al. 2020). NDMI values range from –1 to +1, with high values corresponding to high biomass and water content. The near-infrared (NIR) and short-wave infrared (SWIR) wavelengths are used for determining NDMI. The NDMI values in VTR ranged from –0.142 to 0.565. It was divided into five categories as very low (–0.142–0.065), low (0.065–0.185), moderate (0.185–0.271), high (0.271–0.332) and very high (0.332–0.565). Figure 3c shows the moisture status in VTR. Very high and high NDMI values represented healthy forests with high canopy cover and no water stress and thus were assigned higher



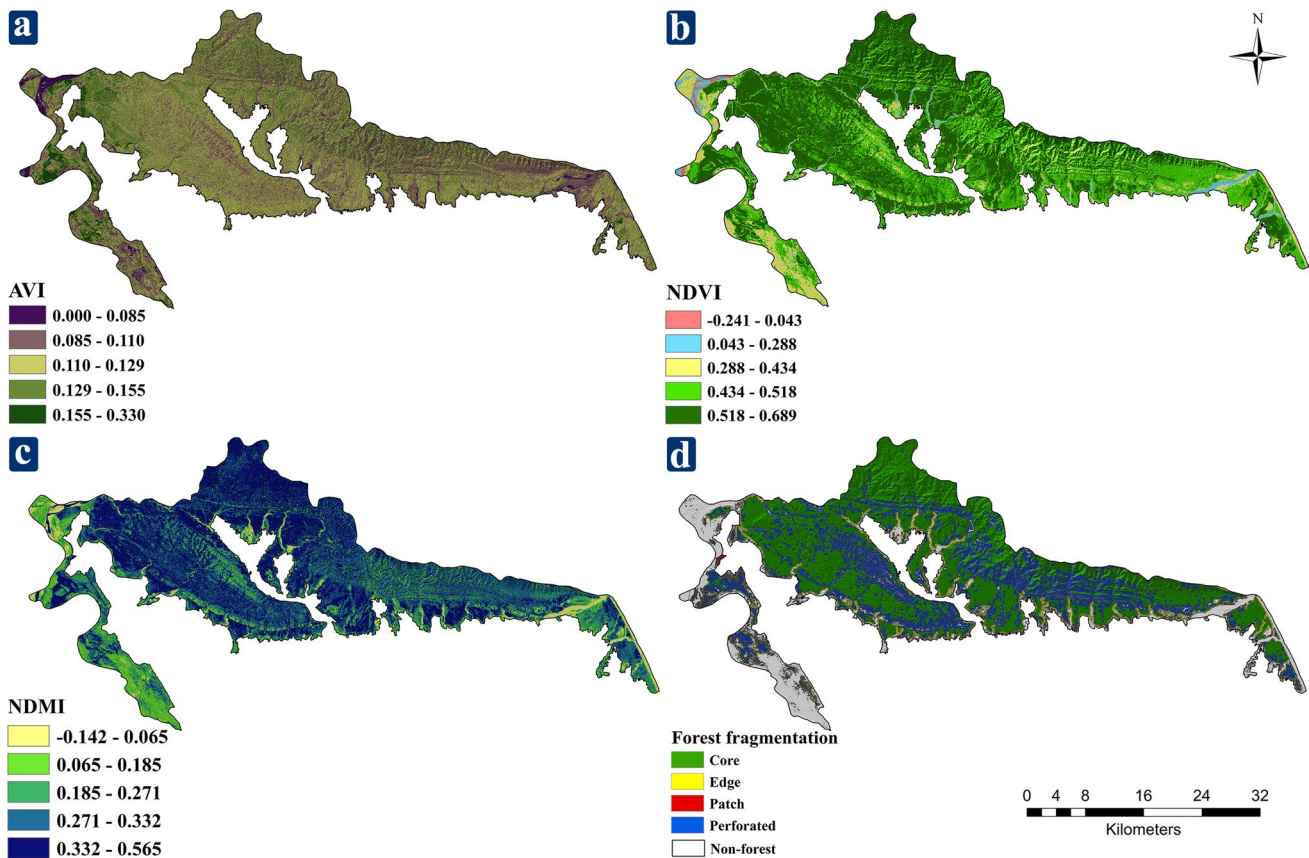
Table 4 Area, weights and rankings of forest health influencing factors

| Sl. No | Factors | Sub-classes | Area | | Categories | Ranking | Fuzzy AHP | |
|--------|----------------------|----------------------------|---------|--------|------------|---------|-----------|----------|
| | | | sq. km | (in %) | | | Weight | W (in %) |
| 1 | AVI | A. 0–0.085 | 38.363 | 4.03 | Very low | 1 | 0.204 | 20 |
| | | B. 0.085–0.11 | 280.301 | 29.46 | Low | 2 | | |
| | | C. 0.11–0.129 | 384.464 | 40.41 | Medium | 3 | | |
| | | D. 0.129–0.155 | 205.432 | 21.59 | High | 4 | | |
| | | E. 0.155–0.330 | 42.723 | 4.49 | Very high | 5 | | |
| 2 | NDVI | A. -0.241–0.043 | 4.216 | 0.44 | Very low | 1 | 0.157 | 16 |
| | | B. 0.043–0.288 | 22.044 | 2.31 | Low | 2 | | |
| | | C. 0.288–0.434 | 107.266 | 11.27 | Medium | 3 | | |
| | | D. 0.434–0.518 | 310.432 | 32.62 | High | 4 | | |
| | | E. 0.518–0.689 | 507.529 | 53.34 | Very high | 5 | | |
| 3 | NDMI | A. -0.142–0.065 | 41.29 | 4.33 | Very low | 1 | 0.138 | 14 |
| | | B. 0.065–0.185 | 87.132 | 9.15 | Low | 2 | | |
| | | C. 0.185–0.271 | 149.431 | 15.7 | Medium | 3 | | |
| | | D. 0.271–0.332 | 298.815 | 31.4 | High | 4 | | |
| | | E. 0.332–0.565 | 374.819 | 39.39 | Very high | 5 | | |
| 4 | Rainfall (in mm) | A. 1232–1311 | 87.633 | 9.21 | Very low | 1 | 0.135 | 13 |
| | | B. 1311–1360 | 230.588 | 24.24 | Low | 2 | | |
| | | C. 1360–1409 | 188.412 | 19.81 | Medium | 3 | | |
| | | D. 1409–1446 | 354.108 | 37.23 | High | 4 | | |
| | | E. 1446–1500 | 90.309 | 9.49 | Very high | 5 | | |
| 5 | Forest fragmentation | A. Non-forest | 178.009 | 18.71 | Very low | 1 | 0.087 | 9 |
| | | B. Patch | 8.755 | 0.92 | Low | 2 | | |
| | | C. Edge | 57.497 | 6.04 | Medium | 3 | | |
| | | D. Perforated | 233.011 | 24.5 | High | 4 | | |
| | | E. Core | 474.137 | 49.85 | Very high | 5 | | |
| 6 | Soil type | A. Calcaric fluvisols (Jc) | 42.547 | 4.44 | Very low | 1 | 0.082 | 8 |
| | | B. Calcic cambisols (Bk) | 29.312 | 3.05 | Low | 2 | | |
| | | C. Dystric Regosols (Rd) | 121.83 | 12.81 | Medium | 3 | | |
| | | D. Eutric Fluvisols (Je) | 331.929 | 34.9 | High | 4 | | |
| | | E. Humic Cambisols (Bh) | 426.137 | 44.8 | Very high | 5 | | |
| 7 | Village | A. 1 km | 42.214 | 4.43 | Very low | 1 | 0.055 | 6 |
| | | B. 2 km | 94.745 | 9.96 | low | 2 | | |
| | | C. 3 km | 96.716 | 10.16 | Medium | 3 | | |
| | | D. 4 km | 102.451 | 10.72 | High | 4 | | |
| | | E. Undisturbed area | 615.705 | 64.74 | Very high | 5 | | |
| 8 | Roads | A. 1 km | 376.677 | 39.6 | Very low | 1 | 0.051 | 5 |
| | | B. 2 km | 184.199 | 19.36 | Low | 2 | | |
| | | C. 3 km | 119.122 | 12.52 | Medium | 3 | | |
| | | D. 4 km | 85.301 | 8.96 | High | 4 | | |
| | | E. Undisturbed area | 185.956 | 19.55 | Very high | 5 | | |
| 9 | Railways | A. 1 km | 27.571 | 2.89 | Very low | 1 | 0.051 | 5 |
| | | B. 2 km | 26.905 | 2.89 | Low | 2 | | |
| | | C. 3 km | 21.401 | 2.25 | Medium | 3 | | |
| | | D. 4 km | 16.768 | 1.76 | High | 4 | | |
| | | E. Undisturbed area | 859.187 | 90.25 | Very high | 5 | | |



Table 4 (continued)

| Sl. No | Factors | Sub-classes | Area | | Categories | Ranking | Fuzzy AHP | |
|--------|---------|---------------------|---------|--------|------------|---------|-----------|----------|
| | | | sq. km | (in %) | | | Weight | W (in %) |
| 10 | Canals | A. 1 km | 30.105 | 3.16 | Very low | 1 | 0.043 | 4 |
| | | B. 2 km | 35.2 | 3.7 | Low | 2 | | |
| | | C. 3 km | 43.494 | 4.57 | Medium | 3 | | |
| | | D. 4 km | 46.259 | 4.86 | High | 4 | | |
| | | E. Undisturbed area | 796.774 | 83.7 | Very high | 5 | | |

**Fig. 3** Factors assessed for forest health:—**a** AVI, **b** NDVI, **c** NDMI, **d** Forest fragmentation

ranks. Very high and high moisture content was found in the forest located in the northern part of the Reserve while the lowest moisture content in forest was recorded in the western and the peripheral parts of the Reserve.

Forest fragmentation

Forest fragmentation is defined as the transformation of continuous forest into isolated forest patches (Bera et al.

2020). In the past few years, the forest ecosystem is being fragmented across the globe for several causes such as road construction, railway construction, agricultural area expansion, increase in urban spaces and development of infrastructural facilities. Forest fragmentation has increased the risk of species extinction and eventually reduced biodiversity. The forest fragmentation was analyzed using the landscape fragmentation tools (LFT v2.0). Land cover was classified using supervised classification into the forest and non-forest classes in ERDAS Imagine 14. Five distinct classes of



forest fragmentation based on specified edge width of 100 m were distinguished in VTR: edge, patch, perforated, core and non-forest. Edge width determines the distance within which other land covers might deteriorate the forest. The core is a moderately far-off region from the edge disturbance and is surrounded by more forest cover. It represents a dense forest that has not been affected hitherto. The perforated area forms the inner boundary of small non-forested areas enclosed by the core forest. The edge represents the marginal region between the core and non-forest areas. In contrast, patches are the emblem of the disturbed category of forest fragmentation. Thus, patch forest is a fragmented ecosystem which occurs due to human encroachment. Figure 3d shows the forest fragmentation in VTR. Of the total forest area of the Reserve (951.049 km²), the largest area was found under core forest (49.85%) followed by perforated (24.50%), patch (6.04%) and edge (0.92%). Non-forest areas accounted for 18.71% of the total area. Figure 4 shows a zoom view of the fragmentation classes in the study area. Non-forest, patch, edge and perforated categories of forests indicated unhealthy forest and were assigned low ranks. Core forest shows healthy forest and was assigned high rank for health condition. The edge and patch located in the buffer zone of the study area show substantial human disturbances.

Rainfall

Rainfall is a crucial component of the hydrological cycle and a significant factor influencing forest health. The productivity of the forest ecosystem requires water nutrients to grow through the process photosynthesis (Gebeyehu and Hirpo 2019). Water stress may increase the susceptibility of trees to various threats. Therefore, rainfall levels can be used to estimate the health condition of the vegetation. Inverse distance weighting (IDW) was used for the interpolation of selected gridded points. The rainfall map was

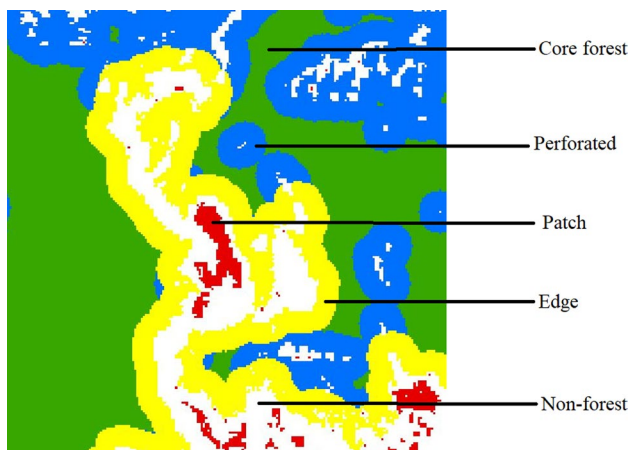


Fig. 4 Zoom view of fragmentation classes in VTR

reclassified into five categories: 1232–1311 mm (9.21%), 1311–1360 mm (24.24%), 1360–1409 mm (19.81%), 1409–446 mm (37.23%) and 1446–1500 mm (9.49%). High rainfall indicated healthy forests and thus assigned high rank of health condition, whereas low rainfall specifies unhealthy forests and are assigned lower ranks. As a whole, the study area receives plenty of rainfall each year, where average rainfall is 1106 mm per year. Figure 5e depicts the rainfall distribution in VTR. The central part of the Reserve receives maximum rainfall (1409–1450 mm), while the southwestern part receives the least rainfall (1232–1360 mm).

Soil type

The soil is an essential component of the forest ecosystem. It helps in regulating critical ecosystem processes such as decomposition, nutrient uptake and water availability (FAO 2015). The interaction between forest and soil helps to ensure that the soil is fertile enough for plant life to continue to grow and flourish (American Forests 2021). The nature of plants and wildlife that supports biodiversity across the globe is determined by the properties of various soils (American Forests 2021). *Bhabar* and *terai* tracts in the VTR containing sediments rich in humus and organic matter are suitable for forest growth. Figure 5f shows the types of soil in VTR. Five major soil types have been identified in the Reserve viz. humic cambisols, eutric fluvisol, dystric regosol, calcareous fluvisol and calcic cambisol. Humic cambisol covered the largest area of the Reserve. Best suitable soil types for forest growth marks healthy forests were given higher ranks while unsuitable soil leads to unhealthy forest were assigned low ranks of forest health conditions.

Distance from village location

A total of 136 villages are located in the buffer zone of the study area (Comptroller and AGI 2018). Five pilgrim shrines existed within the Reserve. These pilgrim sites attract devotee in large numbers every year. The presence of villages indicates heavy anthropogenic pressure on the forest and wildlife. Village location points were randomly extracted from Google Earth Pro, and four buffer zones were created at a distance of 1 km for analyzing the level of disturbance on forests. Total five categories were taken at a distance of 1 km (4.43%), 2 km (9.96%), 3 km (10.16%), 4 km (10.72%) and undisturbed area (64.74%). The lowest ranks were assigned to the highly disturbed area indicating unhealthy forest which lies under 1 km followed by 2 km, 3 km and 4 km accordingly. The highest rank was given to undisturbed area which marks least disturbance of villages representing healthy forests. Figure 5g illustrates village location and multiple buffer zones.

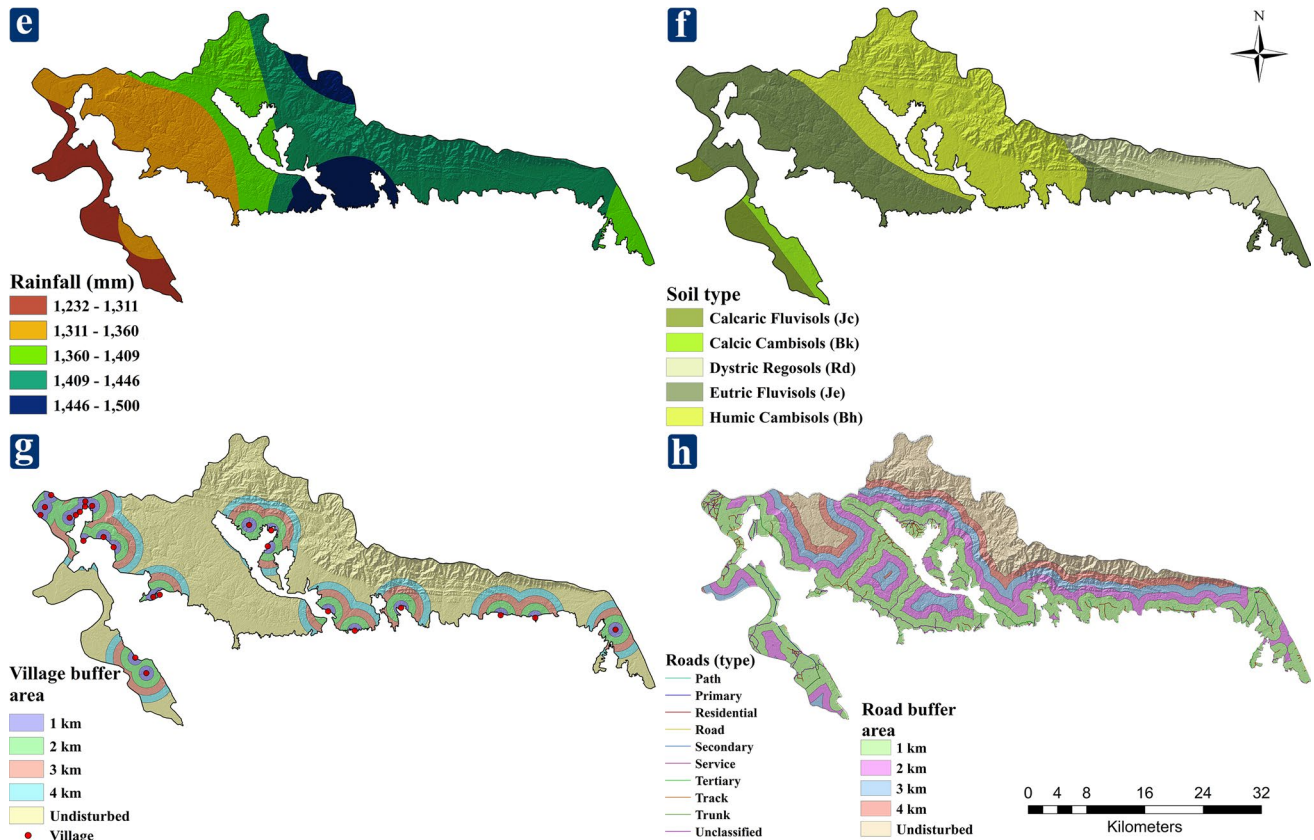


Fig. 5 Factors assessed for forest health:—**e** Rainfall, **f** Soil type, **g** Distance from village locations, **h** Distance from Roads

Distance from roads

Large forest areas are destroyed due to road constructions leading to serious road surface erosion, sediment yield, off-site water pollution, pitfall, direct habitat loss (by turning the natural land cover into an impervious surface) and indirect habitat loss (by the fragmentation of an ecosystem into smaller and more isolated patches). Four buffer zones were delineated to assess the impact of road construction in the Reserve (Fig. 5h). Distance from the roads was further categorized by multiple buffer rings of 1 km (39.60%), 2 km (19.36%), 3 km (12.52%) and 4 km (8.96%) and undisturbed area (19.55%). Highly disturbing buffer zones representing unhealthy forest were assigned low ranks whereas undisturbed area indicates less disturbance of roads and was given high rank.

Distance from railway tracks

Presence of Bagaha-Chhitoni railway line has restricted the movement of animals across the Reserve. National

tiger conservation authority (NTCA) has issued guidelines to restrict the train speeds to 40 km/h during daytime and 25 km/h at night, along with clearing tracks up to a distance of five meters to safeguard the forest habitat and its wildlife (Comptroller and AGI 2018). Four buffers were created in the Reserve for assessing the level of disturbance due to presence of railway lines. These railway lines were further categorized by multiple buffer rings at a distance of 1 km (39.60%), 2 km (19.36%), 3 km (12.52%), 4 km (8.96%) and undisturbed area (19.55%). Figure 6i shows major railway lines across VTR. The buffer area of eastern and western part of the Reserve is significantly impacted by the railway lines. The highly disturbed zones impacting forests were given low ranks whereas undisturbed area was given high rank.

Distance from canals

Forest reserve is also stressed severely due to the construction of dams, barrages and canals. For example, the Gandak barrage is located in the Valmiki Nagar range,

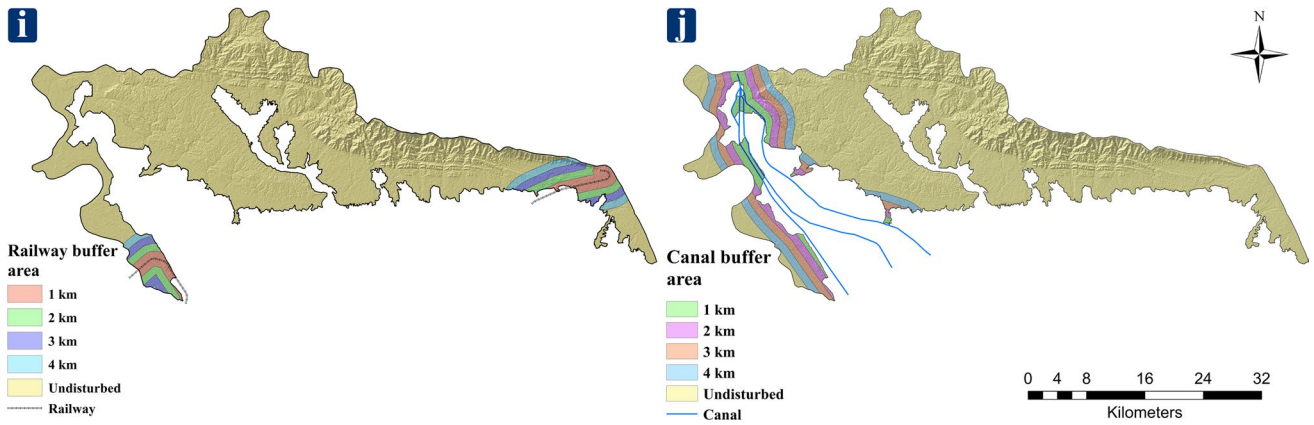


Fig. 6 Factors assessed for forest health:—i Distance from railway tracks, j Distance from canals

whereas *Sikpiya* and *Tirhut* canal are situated at the *Madanpur* forest range. Buffers of canals were created at a distance of 1 km (2.89%), 2 km (2.82%), 3 km (2.25%), 4 km (1.76%) and undisturbed area (90.34%) (Fig. 6j). The western part of the Reserve is highly impacted by barrages and canals. The high rank was given to undisturbed area representing healthy forests. The lowest ranks were given

to the highly disturbing buffer zones indicating unhealthy forest.

Forest health identification

Forest Health map depicts relative quantities of forest vegetational stress. The forest health map of VTR was classified into four classes: unhealthy forest (120.576

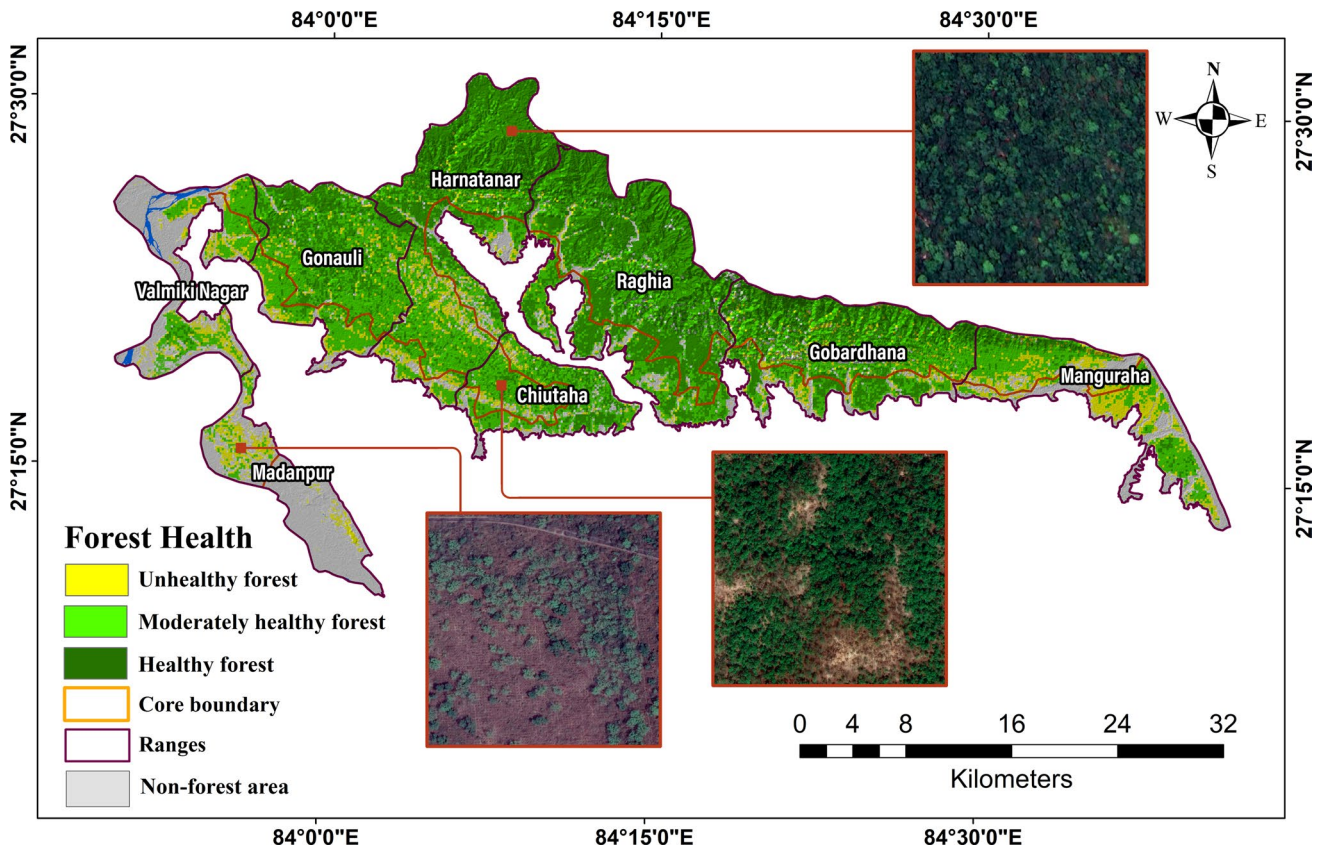


Fig. 7 Forest health map

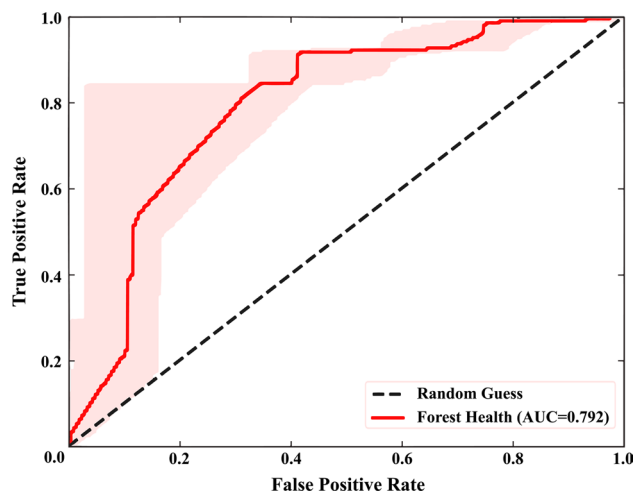
Table 5 Area under different classes

| Forest Health | Area sq. km | % |
|---------------------------|----------------|-------|
| Unhealthy forest | 120.576 | 12.67 |
| Moderately healthy forest | 350.592 | 36.86 |
| Healthy forest | 294.861 | 31.00 |
| Non-forest | 185.02 | 19.47 |
| Total area | 951.049 | 100 |

km²), moderately healthy forest (350.592 km²), healthy forest (294.861 km²) and non-forest (185.02 km²) (Fig. 7). In VTR, the largest area is covered with moderately healthy forest (37%), followed by healthy forest (31%) and unhealthy forest (13%), respectively. The remaining 19% of the Reserve comes under non-forest including agriculture fields, settlements, water bodies, sand beds and barren lands. Forests with minimal stress are generally formed by healthy vegetation. In contrast, unhealthy forests show dry or dead plant material, excessively sparse canopy and poor light usage in high-stress circumstances. Table 5 presents category-wise forest health map statistics. VTR spreads over eight ranges. Unhealthy forest is found in the ranges of *Valmiki Nagar*, *Madanpur* and eastern part of *Manguraha*, located in the buffer zone of the Reserve. These ranges are extremely disturbed due to human inhabitation where several villages, connected roads, *Gandak* barrage and farmlands were noticed. The largest area of the Reserve is covered with moderately healthy vegetation, sited in almost all the ranges. This forest class consists of mainly open forest, grasslands, wetlands, plantations and patches with grasses. *Gonauli*, *Chiutaha*, *Gobardhana*, *Manguraha* and southern part of *Harnatanar* range are mostly covered with moderately healthy vegetation. The perforated fragments have also been located in these ranges. Healthy forest tracts are found in *Raghia* and northern part of *Harnatanar*, *Gonauli* and *Gobardhana* ranges. Dense forests are dominated by deciduous *Sal* and *Chir*, located at high elevation with minimal or negligible human disturbances. The forest of these ranges is least affected and comparatively less disturbed. Since the forest quality of VTR was found stable to some extent, however, unhealthy and moderately healthy vegetation should be given more consideration for conserving them effectively.

Validation

The prepared forest health map of VTR was validated with 200 sample points taken from google earth through

**Fig. 8** Receiver operating characteristics (ROC) curve assessment for forest health

AUC-ROC curve (Fig. 1). The ROC curve shows a true positive rate vs a false positive rate for different cut-off points of a variable (Mukherjee and Singh 2020). The validation result indicates good prediction using the FAHP process. In the present study, the ROC curve with an AUC value of 0.792 shows that the prepared forest health map is acceptable (Fig. 8).

Discussion

A healthy forest is the state of forest that serves economic, environmental and socio-cultural purposes over space and time. However, forests are susceptible to constant exploitation and deterioration due to anthropogenic intensification and interferences. Therefore, forest health is being increasingly addressed worldwide as a notion of forest management. Currently, the health evaluation for forest ecosystems focuses on three significant aspects, i.e., vitality, organizational structure and resilience. Himalaya and its surrounding terrains are extremely sensitive to geohydrology, where climatic factors influence the sustainability of the mountain ecosystem. The terai arc landscape is located in the shadow of the Himalayas. This landscape is fragile where forest fragmentation is a prominent disturbing factor. The ecosystem of VTR has a rich biodiversity; however, biotic pressure and developmental activities have induced fragmentation of natural habitats which leads to degradation of the forest ecosystem. Similar impacts of fragmentation were also observed in *terai* landscape by Das et al. (2017) and Sharma et al. (2020a, b) who attributed agricultural expansion, road construction and population pressure were the main reasons. The Reserve experiences episodes of flooding and soil erosion which leads to forest deterioration. Modification and

altering in the course of the *Gandak* River and its path pose one of the region's most crucial threats. However, human-induced disturbances are more prevalent in VTR including agriculture expansion, illegal felling of trees for local needs and commercial purposes, collection of non-wood forest products, livestock grazing and forest fires in the fringe areas of the Reserve. Similar findings were also observed by Lu et al. (2021) where human activities have induced forest fragmentation in forest farms in Beijing.

Several vegetation indices (VIs), depending on the spectral reflectance of the sensors, have been utilized in past studies to measure quantitative and qualitative vegetation characteristics (Barka et al. 2018; Dutta et al. 2020; Kayet et al. 2020; Lausch et al. 2016; Sharma et al. 2021). The present study utilized direct and indirect factors and their level of disturbance impacting the health of the forest ecosystems in VTR. AVI shows vegetation density of the Reserve and, thus, is given high priority than other factors. NDVI index was set forth for canopy evaluation of the study area. Mahato et al. (2021) and Halder et al. (2021) have also reported NDVI as an effective vegetation index to assess forest health status. NDMI was used to assess the moisture content and physiology of the vegetation in VTR. Lastovicka et al. (2020) and Dutta et al. (2021) determined NDMI as a suitable indicator to detect the disturbances in the forest and their impact on forest health. Forest fragmentation was used to analyze the edge effect as it disturbs wildlife habitat and reduces forest health to a great extent. The findings of the present study are in tune with Dutta et al. (2017), Jain et al. (2016), Shapiro et al. (2021) and Sahana et al. (2015). Their studies demonstrated the effectiveness of the forest fragmentation approach in monitoring and examining forest health dynamics at various geographical scales. Soil type data indicated the soil fertility of the area significantly affects trees' growth, vitality and health. Rainfall was used to evaluate vegetation status and its comprehensive growth. Multiple buffer rings of village location, roads, railways and canals manifested the degree of anthropogenic disturbance in forest cover of VTR. Ray et al. (2021) and Sam (2021) have also suggested quantifying the level of disturbances in forests to examine forest health dynamics.

Of the total area of the Reserve, 37% of the forest area was found under moderately healthy category. Moderately healthy forest was mainly found in buffer zone. This zone of the Reserve consists of a relatively thin patch of forest with extensive exploitation by the local population. Several villages are located at the fringe of the buffer zone and are highly subjected to biotic pressure. The local population relies on the forest for fodder, fuelwood, bamboo and timber. Sand mining and extraction of stones or boulders from river beds and *bhabar* deposits are carried out at various locations by villagers in an illegal manner. The healthy forest category comprises 31% of the total forest area mostly located in the

core area of the VTR. Lu et al. (2021) also reported that the core area has healthy vegetation due to the non-intervention of human activities. The core area of the Reserve has minimal or negligible human activity because of less or no connectivity of roads and others. The government also prohibited the large-scale cutting of trees as it lies in the core and at higher elevations. The segment of unhealthy forests (13%) is extensively disturbed forests. This category of forest is highly disturbed by local population and tourists. The undergrowth vegetation is also limited in this area. Extensive settlements, agricultural fields, high livestock grazing and development of public infrastructures, such as roads, railways, markets, religious sites, power lanes and mobile towers, have been widely employed in the peripheries of buffer zone exerting interference with pressure (Fig. 9). Illegal cutting of cane and timber was also carried out in the fringe areas. The forest tracts of *Madanpur* range of VTR is suitable for tiger habitat and other herbivores; despite that, it is entirely fragmented from the Reserve due to development of roads, railways and settlements and considered as unhealthy forest (Fig. 10). Besides, several invasive weeds, such as *Eupatorium Parthenium*, *Mikania*, *Lantana* and *Van Tulsii*, have also infested many parts of the Reserve resulted due to improper management practices, biotic intervention and the recurrence of the uncontrolled forest fire.

The Government of Bihar has undertaken several plans for efficient management of forests in the State. Wildlife and their habitat are being protected by the dynamic engagement of individuals employing in eco-development committees (BAPCC 2015). The State has extended its foresting activities to achieve its goal by implementing programs for agroforestry such as *Krishi Vaniki Yojana* and *Mukhyamantri Niji Paudhashala yojana* and similar efforts under the *Hariyali Mission* in Bihar to enhance the forest and trees outside forests (Yadav 2019). The Bihar Climate Change Action Plan (BAPCC) aims to deal with climate change by improving carbon sinks in forestry and other ecosystems, increasing the resilience of vulnerable species/ecosystems to adapt themselves to changing climates and making it possible for local communities to adapt to climate variability. The open international border with Nepal, encroachment, intense local pressure, weed invasion and severe soil erosion pose the foremost challenges in VTR management (NTCA 2020). Exploring transborder conservation opportunities and cooperating with the National Park of the Royal Chitwan of Nepal in the social forests and agroforestry sectors should be encouraged to restore forest stability. Sharma et al. (2020a, b) and Talukdar and Sinha (2013) have reported the capabilities of Indo-Nepal transborder initiatives for the effective management of protected areas across the border. Relocation of villages from the Reserve must be taken into consideration in order to avoid human-wildlife conflicts. The forest-dependent communities should be supported with alternative



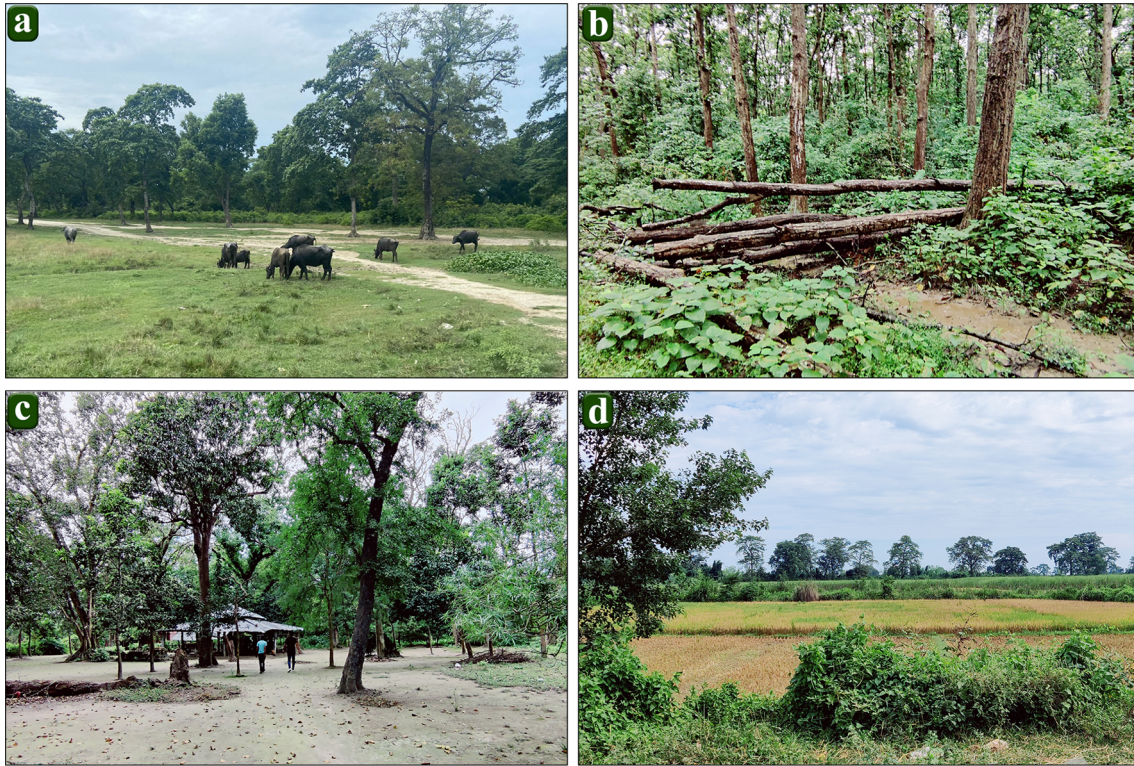


Fig. 9 Forest deterioration in VTR through: **a** Livestock grazing, **b** Illegal logging, **c** Religious site, **d** Agriculture fields



Fig. 10 Forest fragmentation in VTR through: **a** Roads, **b** Settlements, **c** *Gandak* barrage



means of sustainable livelihoods, such as social forestry or horticulture to lessen their dependency on the forest. Jain and Sajjad (2015) have also suggested the relocation of local communities in the Sariska Tiger Reserve of India to reduce their livelihood dependency on forests. The involvement of local population in conservation measures and eco-tourism should be highly encouraged. The weeds removal, invasive species, retention of soil moisture and management of grassland in VTR should be included in continuous management practices. Appropriate research and monitoring of the Action Plan on Climate Change and interdepartmental coordination to promote biodiversity and forest sustainability must be prioritized. Efficient measures are required to improve forest conditions and proper monitoring to facilitate early detection and response.

Conclusion

The present study evaluated the forest health condition of Valmiki Tiger Reserve in India. Direct and indirect influencing factors were integrated to prepare forest health map. These factors were given weightage through FAHP based on their relative significance. The forest health map was classified into four classes namely healthy forest, moderately healthy forest, unhealthy forest and non-forest. The largest area of the VTR was found under moderately healthy forest (37%) category followed by healthy forest (31%) and unhealthy forest (13%). The non-forest class covers 19% of the total Reserve including barren land, agricultural land, built-up and water bodies. The moderately healthy forest is mainly concentrated in *Gonauli*, *Chiutaha*, *Gobardhana*, *Manguraha* and *Harnatanar* ranges of the Reserve. Moderately healthy forest tracts are susceptible to various anthropogenic activities and fragmentation. Comparatively, less disturbance has been observed in the core areas of the Reserve. *Raghia*, *Gobardhana* and northern part of *Gonauli* and *Harnatanar* ranges have healthy forest tracts due to higher elevation with less anthropogenic disturbances. The precipitation is recorded relatively higher in these ranges. Unhealthy forest tracts are found in the *Valmiki Nagar*, *Madanpur* and eastern part of *Manguraha* ranges, which lies in the buffer zone of the Reserve. High disturbance has been observed in these ranges due to presence settlements, agricultural fields, water bodies, roads and railway lines. The validation of the forest health map was carried out by the AUC-ROC curve. The AUC value (0.792) shows the acceptability of the result. Analyzing disturbing factors allowed to have a deep insight of the indirect activities affecting forest health dynamics. Public awareness through educational programs and including local stakeholders in decision-making policies should be encouraged to minimize natural and anthropogenic effects on the forest ecosystem. Geospatial

technology and MCDM approaches have proved useful for assessing forest health using remote sensing-based indicators. However, the other indirect factors namely, logging, mining and grazing which have much influence on protected areas should be taken into consideration for analyzing relationship between forest health and disturbances. It is argued that such type of assessments utilizing remote sensing data and site-specific influencing factors may help in effective forest management planning. Further, continuous monitoring of forest health, forest-dependent communities' participation, relocation of villages, human-wildlife conflicts and management of grasslands are some of the priority areas for the future studies. The findings of the present study may help planners, policymakers and local stakeholders for proper monitoring and devising sustainable management practices across the Reserve.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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