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Spatio-temporal assessment of vegetation health using satellite-based multi-spectral indicators in Hamirpur District of Uttar Pradesh, India

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Abstract. Vegetation health is an essential indicator in assessing ecosystem stability, environmental sustainability and resistance to climatic stress, especially in semi-arid regions. In this study, the spatio-temporal variation of vegetation health was evaluated between 2015 and 2025 in Hamirpur District of Uttar Pradesh, India, using multi-spectral remotely sensed data. Seven satellite-derived parameters, including the Normalised Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), Normalised Difference Moisture Index (NDMI), Normalised Difference Red Edge Index (NDRE), Chlorophyll Index (CI) and Land Surface Temperature (LST), were used to assess vegetation health. These indicators were conceptually grouped into four dimensions: vegetation vigour (NDVI, EVI and SAVI), moisture status (NDMI), physiological/chlorophyll condition (NDRE and CI) and thermal stress (LST). Principal Component Analysis (PCA) was applied to weight the indicators objectively, and a GIS-based weighted overlay method was used to create a composite Vegetation Health Index (VHI). The first principal component accounted for 86.69% of the total variance. The result shows a significant improvement in the vegetation condition, with a mean VHI of 0.331 in 2015, 0.543 in 2020, and 0.633 in 2025. There was a significant decrease in Very Poor (−58.96%) and Poor (−24.25%) vegetation health classes, while there was a remarkable increase in Healthy (+175.60%) and Very Healthy (+310.09%) classes. Seasonal analysis also showed strong resilience of vegetation, especially during winter and post-monsoon. The VHI model was well validated with the secondary data sources. The results show the potential of multispectral, red-edge, moisture and thermal data for vegetation health monitoring and offer valuable knowledge for ecosystem management, climate change adaptation and sustainable environmental planning in semi-arid environments.

Key words:
VHI,
Remote Sensing,
PCA,
Weighted Overlay Analysis,
Bundelkhand,
India

Introduction

Vegetation is an integrated part of terrestrial ecosystems and critical for ecological balance, climate change moderation, biodiversity, soil and water protection and agricultural production. Vegetation condition and health change with space and time, acting through climatic, hydrological, edaphic and anthropogenic factors (Ahlström et al. 2015; Han et al. 2022). The degradation of vegetation may increase environmental vulnerability, reduce biodiversity and soil stability and exacerbate erosion, while healthy vegetation plays a substantial role in carbon sequestration, soil cycling and ecosystem resilience (Wang et al. 2007). In light of climate change, land degradation and increasing pressure on natural resources, it has

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become increasingly important to monitor vegetation health (Rao et al. 2023; Pérez-Aguilar et al. 2026).

The traditional approaches to assessing vegetation health are based mainly on field observations and on-site surveys. The development of remote-sensing technology has revolutionised the way vegetation health is monitored because it provides synoptic (whole area), repetitive and continuous observations of Earth's surface (Li et al. 2023). Satellite imagery is an effective way to monitor the state of vegetation on a large spatial and temporal scale and will be essential for monitoring and sustainable management of the environment (Lausch et al. 2018).

The spectral characteristics of vegetation can give useful data on the physiological and biochemical state of vegetation. Multispectral satellite data are commonly used in the development of vegetation indices to assess vegetation vigour, biomass, chlorophyll content, moisture availability and stress conditions (Kureel et al. 2022). With these indicators, the Normalised Difference Vegetation Index (NDVI) is still one of the most widely used indicators to evaluate the greenness of vegetation and photosynthetic activity (Huang et al. 2021). NDVI is based on the difference between reflectance in the red and near-infrared wavelengths and is used to measure vegetation density and productivity. But it is less sensitive in areas where there is a high vegetation canopy because of saturation effects.

Given that the NDVI had some drawbacks, the Enhanced Vegetation Index (EVI) was created to increase sensitivity in areas of high biomass and minimise the bias of the canopy background and atmosphere (Ambika and Mishra 2019). Similarly, the Soil Adjusted Vegetation Index (SAVI) accounts for the effect of bare soil with an adjustment factor, which is very useful for semi-arid and barren areas (Chowdhury et al. 2024). These vegetation indices can be combined for complementary information about the structure, productivity and canopy condition of the vegetation.

Normalised Difference Red Edge Index (NDRE) is another index that has been found to be a good indicator of the concentration of chlorophyll and plant physiological status. The red-edge wavelengths are very sensitive to changes in chlorophyll content, so this makes NDRE a good indicator of vegetation stress before visible symptoms occur (Daglio et al. 2022). The Chlorophyll Index (CI) also gives direct information on leaf chlorophyll concentration, nutrient status, and photosynthetic capacity (Kumar et al. 2025). The chlorophyll content is closely related to the vitality and productivity of vegetation, and these indications are especially useful for assessing the health of vegetation.

Another important factor that determines the health of vegetation is moisture availability. Water stress can have a profound impact on photosynthesis, growth and the sensitivity of vegetation to environmental disturbances. Normalised Difference Moisture Index (NDMI) is often utilised to evaluate the water content of vegetation and the moisture status of the vegetation canopy (Varouchakis et al. 2025). The use of shortwave infrared data allows NDMI to provide some information on the moisture status of vegetation, making it a valuable tool for detecting drought stress and ecosystem resilience. In semi-arid areas, where water is often a limiting factor for vegetation growth, moisture dynamics are particularly relevant (Dutta et al. 2021).

Thermal conditions play a significant role in vegetation performance, along with vigour of vegetation, chlorophyll content and moisture availability. High land surface temperature can lead to higher evapotranspiration, higher moisture stress and lower vegetation productivity (Dapke et al. 2025). Thermal satellite-derived Land Surface Temperature (LST) is therefore an important parameter to monitor environmental stress and vegetation condition. Combining thermal data with MS vegetation indices offers a better understanding of vegetation responses to climatic variability and climatic stress (Afshari et al. 2025).

Vegetation health is multidimensional and, therefore, requires the use of multiple indicators, not just one. Various indices reflect various aspects of vegetation functioning such as greenness, productivity, chlorophyll content, moisture status, and thermal stress (Kundu et al. 2016; Gidey et al. 2018; Singh et al. 2024b). This has led to the emergence of composite vegetation health assessment, which has been receiving significant attention in environmental monitoring research. When the number of variables is large and there is a high degree of correlation between the variables, multivariate statistical methods like Principal Component Analysis (PCA) can be used to reduce the number of variables to a few independent variables (Ashraf et al. 2023). PCA allows for the reduction of data redundancy, extraction of dominant patterns of variation and determination of indicator weights to be performed in an objective manner. It thus offers a solid basis for combining

several indicators derived from remote-sensing data to form a Vegetation Health Index (Qamar et al. 2022; Samsuddin et al. 2025).

Spatial overlay techniques are also used with Geographic Information Systems (GIS) to improve vegetation health evaluation. Overlay analysis is a method that combines several standardised indicators in one spatial framework and allows the identification of areas of healthy vegetation, degraded areas and environmentally stressed areas (Bera et al. 2020; Chauhan et al. 2025). The use of PCA-derived weights and GIS-based weighted overlay methods offers a systematic and transparent way to assess vegetation health in diverse landscapes. Integrated methodologies are useful for spatial decision-making and for monitoring environmental changes over time (Das et al. 2022).

In this context, satellite-derived multispectral indicators provide a valuable tool to assess vegetation health at the district level of Hamirpur. Principal component analysis and GIS-based overlay analysis of associations of the different NDVI, EVI, SAVI, NDRE, Chlorophyll Index, NDMI and LST indices allow for a comprehensive assessment of vegetation condition, capturing both structural, physiological, hydrological and thermal aspects of ecosystem health. This will help to improve our knowledge of vegetation dynamics and aid in evidence-based environmental planning and sustainable land use in semi-arid regions.

Literature review

Vegetation health is a multi-dimensional ecological phenomenon, and reliance on a single vegetation index has been superseded by the use of multiple indices. Numerous studies have shown that there are complex relationships between vegetation productivity, moisture availability, physiological condition and environmental stress that are not reflected in a single indicator (Porporato et al. 2001; Liu et al. 2020; Green 2024). Many studies have shown that satellite-derived vegetation indicators are good proxies for seasonal and interannual changes in vegetation conditions and are useful for estimating how an ecosystem is reacting to climate change and anthropogenic disturbance (Maignan et al. 2008; Huang et al. 2019; Zeng et al. 2022). The value of remotely sensed vegetation indicators for detecting environmental stress before observable changes are noticed on the ground was shown by Rao et al. (2023). Zhou et al. (2023) found that, in semi-arid ecosystems, ecological reactions to climatic stress can be spatially very heterogeneous, highlighting the importance of having frameworks for monitoring that are area-sensitive to the area, where localised areas of vulnerability and resilience can be identified. The empirical studies of Mehmood et al. (2024) and Wang et al. (2007) have revealed that the use of the greenness indicators together with moisture and thermal variables significantly enhances the detection of vegetation stress. Therefore, it is important to consider the integration of optical and thermal indicators in order to get a complete picture of vegetation conditions. Studies consistently find that multi-indicator frameworks are better than single index methods at detecting stressed vegetation and degraded landscapes (Kureel et al. 2022; Haq et al. 2023; Alqadhi et al. 2025). Barbosa et al. (2015), Nzabarinda et al. (2021) and Yang et al. (2022) have shown a high positive correlation between vegetation growth and precipitation, especially in water-limited environments. Variability in rainfall consistently emerged as a key factor in vegetation productivity and ecosystem function when analysed on a long-term basis over a range of semi-arid landscapes. According to Dapke et al. (2025), temperature is also proving to be an important determinant of vegetation dynamics. Although moderate warming can stimulate vegetation growth in some areas, high temperatures can increase evapotranspiration and moisture stress, resulting in vegetation health deterioration.

Recently, several methods have been used to develop composite indices, such as multivariate analysis, statistical aggregation and weighted linear combinations (Abdi and Williams 2010; Kharat et al. 2016). Among these, PCA is one of the most commonly used. Many studies have shown that PCA can be an effective dimensionality reduction technique that retains most of the information in correlated datasets (Bro and Smilde 2014; Greenacre et al. 2022, 2023). Spatial data integration of multiple environmental variables has become essential and is achieved by GIS. Overlay analysis has been extensively used in ecological vulnerability, land suitability, environmental risk and vegetation health assessment studies (Rathore et al. 2016; Karimi et al. 2019; Mahmoody Vanolya and Jelokhani-Niaraki 2021).

Weighted overlay has been shown to integrate multiple datasets geographically and to retain geographic variance. These methods have been especially helpful for identifying "hotspots" in the environment and for spatial planning efforts. Incorporating weights derived from statistical methods with GIS-based overlay techniques has further enhanced the reliability and transparency of composite environmental assessments.

Research gap

Although remote sensing has been widely applied in vegetation monitoring, most of the studies have focused on single vegetation indices, like NDVI, for vegetation condition assessment (Mahajan and Bundel 2016; Kumar et al. 2025; Varouchakis et al. 2025). Often, these methods are inadequate for addressing the many facets of vegetation health, which are affected by vegetation vigour as well as chlorophyll levels, moisture availability and thermal stress. Additionally, a reliable spatio-temporal evaluation of vegetation health is still limited in semi-arid regions, where vegetation is sensitive to environmental stress and climatic variability, and where extensive vegetation health assessment is difficult due to heavy reliance on statistical weights and integration techniques in GIS. Hence the need for a comprehensive framework for robust vegetation health assessment based on multiple satellite-derived indicators, more aptly expressed by PCA and spatial overlay techniques, that would be able to assess the vegetation dynamics and health conditions over time.

Objectives

1. To assess the spatio-temporal dynamics of vegetation health in Hamirpur District from 2015 to 2025 using satellite-derived vegetation, chlorophyll, moisture and thermal indicators.
2. To develop a composite VHI by integrating seven satellite-derived indicators representing four dimensions: vegetation vigour, moisture status, physiological/chlorophyll condition and thermal stress, through PCA and GIS-based weighted overlay techniques.

Study area profile

Hamirpur district is geographically located between latitudes 25°7'N to 26°7'N and longitude 79°17'E to 80°21'E, and has an area of 4121.9 km^2 and an elevation from 80 m above mean sea level and explicitly bounded by Jalaun, Kanpur and Fatehpur districts to the north, Banda to the east, Mahoba to the south and Jhansi and Jalaun districts to the west. The socio-economic scenario of the area includes a population of 1,104,285 (593,537 males and 510,748 females), with the population being primarily rural (81%), a population density of 268 persons/km^2 and a decadal growth rate of 5.78%. This unique terrain is formed by the critical interaction of the rivers Yamuna and Betwa and smaller tributaries such as the Barma and the Ken and is structurally defined by Bundelkhand soil profiles (adhesive Mar black cotton soil and Kabar soil, lighter Parua and gravelly Rakar soils over the undulating landscape). The district has a sub-tropical, semi-arid climate with annual average rainfall of 840 mm, peaking during the monsoon. The district experiences a minimum temperature of 4 °C in January and a maximum of 47.8 °C in May. This climate is conducive to the formation of a Tropical Dry Deciduous Forest ecosystem and the scrub dominated by hardy, drought-resistant species like Dhauk, Palas (Flame of the Forest), Khair and Babool, as well as native species of trees including Neem, Mahua, Ber and an invasive species of trees, Vilayati Babool, which stabilises the riverine ravines. The location of the study area is presented in Figure 1.

Description of the dataset

In this study, multi-source satellite data from Landsat-8/9 and Sentinel-2 were employed to evaluate vegetation health for the period 2015–25. The multispectral and thermal observations obtained from these satellite data are high quality and are used widely for monitoring the environment, assessing vegetation and characterising the land surface.

Vegetation, moisture and thermal indices were derived using Landsat-8 and Landsat-9 satellite images downloaded from the United States Geological Survey (USGS) Earth Explorer, an open-source platform. The Landsat missions include the Operational Land Imager (OLI) and Thermal Infrared Sensor

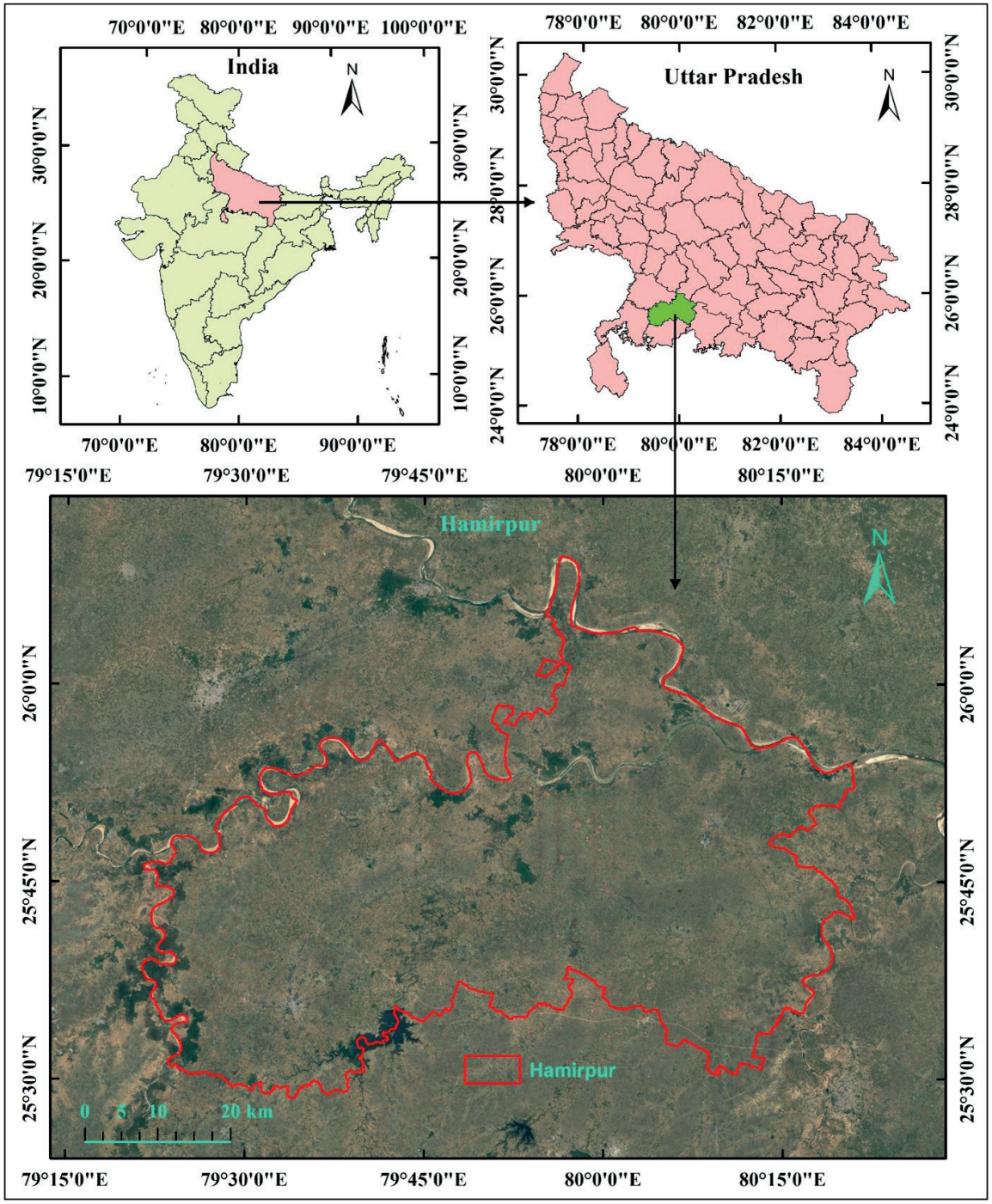


Fig. 1. Location of the study area

(TIRS), which observe the Earth in multispectral bands at 30-m spatial resolution and in thermal bands at 100-m resolution, both resampled to 30 m for analysis. The nature of these datasets makes them ideal for long-term environmental studies because of the temporal span and radiometric consistency of these datasets.

The vegetation physiological parameters were obtained from Sentinel-2 images for extracting the NDRE and CI. The Multi-Spectral Instrument (MSI) sensor onboard Sentinel-2 satellites is equipped with red-edge bands to support vegetation monitoring and chlorophyll estimation. Depending on the spectral band, the spatial resolution of the imagery provided by the MSI sensor is 10 m, 20 m and 60 m,

Table 1. Description of dataset used in the study

No.	Indicator Name	Satellite Name	On-Board Sensor	Spatial Resolution	Source
1	LST	Landsat-8/9	OLI/TIRS	100m×100m for Thermal Bands; 30m×30m for Other Bands	https://www.usgs.gov/landsat-missions/landsat-8
2	NDVI EVI SAVI NDMI	Landsat-8/9	OLI/TIRS	100m×100m for Thermal Bands; 30m×30m for Other Bands	https://www.usgs.gov/landsat-missions/landsat-8
3	NDRE CI	Sentinel-2	MSI	10m×10m, 20m×20m and 60m×60m	https://dataspace.copernicus.eu/data-collections/copernicus-sentinel-missions/sentinel-2

allowing detailed analysis of vegetation condition and stress responses. All the essential details are given in Table 1.

Data preprocessing

The satellite image was processed before the extraction of vegetation health indicators to ensure consistency, accuracy and comparability of the data across time. The imagery acquired was initially radiometrically corrected from raw digital numbers (DN) to physically meaningful values of surface reflectance (Krisbiantoro et al. 2024). This process reduced the distortions and changes in illumination conditions caused by the sensors and thus made the spectral measurements more reliable. Satellite atmospheric correction was applied to remove the effects of atmospheric constituents like aerosols and water vapour and scattering effects that can alter the spectral response recorded by the satellite sensor (Yin et al. 2022). The pre-processing helped to improve the representation of the actual ground surface conditions and also allowed for comparison between images over time. Spectral information was not contaminated by clouds and cloud shadows, which were identified and masked.

Methods

Calculation of LST

LST was derived from TIRS Band 10 of Landsat 8/9 following a multi-step procedure involving the conversion of DN to top-of-atmosphere spectral radiance, radiance to brightness temperature, estimation of land surface emissivity and computation of final surface temperature.

1. Conversion of DN to Top-of-Atmosphere Spectral Radiance (Morrison et al. 2023). The digital number values were converted to spectral radiance using the following Eq. 1:

$$L_\lambda = M_L \times Q_{cal} + A_L \quad (1)$$

where L_λ = TOA spectral radiance, Watts/m^2×srad×μm, ML = Band-specific multiplicative rescaling factor from the metadata, $Qcal$ = the raw Digital Number (DN) value of the pixel and A_L= Band-specific additive rescaling factor from the metadata.

2. Convert TOA into Brightness Temperature (BT): BT is the temperature of a theoretical blackbody. It assumes the Earth's surface is a perfect emitter of radiation (Dubey et al. 2025). We use the thermal constants provided in the metadata file. It has been calculated using the following Eq. 2:

$$BT = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} - 273.15 \quad (2)$$

where BT = Brightness Temperature in Celsius, K_1 and K_2 = Band-specific thermal constants from the metadata and ln = Natural logarithm.

3. Calculate Fractional Vegetation (P_v) and Emissivity (ε): Next, we calculate the Fractional Vegetation, which determines the proportion of mixed pixels covered by vegetation versus bare soil. It has been calculated using the following Eq. 3 on NDVI data (Mahata et al. 2024):

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \quad (3)$$

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4. Land Surface Emissivity (ε) calculation: Emissivity is a factor between 0 and 1 that scales how efficiently a surface emits thermal energy compared to a perfect blackbody (Nse et al. 2020). It was obtained using the following Eq. 4:

$$\varepsilon = 0.004 \times P_v + 0.986 \quad (4)$$

where 0.986 = the standard emissivity of a fully vegetated surface and 0.004 = the standard deviation/soil correction factor.

5. Calculation of final LST: Finally, we combine the BT and ε to calculate the true LST. This formula corrects for the fact that the Earth's surface is not a perfect blackbody. The final LST calculation was done using the following Eq. 5 (Sahak et al. 2023):

$$LST = \frac{BT}{1 + \left(\frac{\lambda \times BT}{\rho}\right) \times \ln(\varepsilon)} \quad (5)$$

where λ = Wavelength of emitted radiance (for Landsat Band 10, this value is approximately 10.89 μ"m)" , ρ = this is a constant, which is calculated using Eq. 6:

$$\rho = h \times \frac{c}{\sigma} = 1.438 \times 10^{-2}\ \mathrm{m \cdot K} \quad (6)$$

where h = Planck's constant (6.626×10^{-34}J·s), c = Velocity of light (2.998×10^{8} m/s) and σ = Boltzmann constant (1.38×10^{-23} J/K).

Calculation of multi-spectral indices

A set of multi-spectral vegetation indices that represent biophysical and physiological characteristics of vegetation was derived from Landsat-8/9 and Sentinel-2 satellite imagery. The indices were chosen because greenness of the canopy is not the only factor that represents vegetation health; other factors include moisture availability, chlorophyll concentration, nutrient status and environmental stress conditions. Each index reflects a particular facet of vegetation function, and ecosystem status is more effectively gauged using multiple indices than a single index.

NDVI (Eq. 7) was used for evaluation of the vegetation density, greenness and photosynthetic activity. One of the most commonly used vegetation cover and productivity indicators for monitoring vegetation cover and productivity, NDVI provides information on aggregate vegetation vigour within the study area (Vaiphasa et al. 2011). To enhance the sensitivity in relatively dense vegetated regions and reduce atmospheric and background noise, EVI (Eq. 8) was added. EVI is especially valuable for understanding biomass and canopy structure and can be used alongside NDVI for vegetation health assessments (Huang et al. 2019).

To remove the effects of bare ground on vegetation assessments, SAVI (Eq. 9) was used. The index is particularly significant in semi-arid regions, like Hamirpur, where the coverage of vegetation is low and soil is exposed, which can cause traditional vegetation indices to yield misleading values. The addition of SAVI allows for better representation of vegetation conditions in areas with variable land cover (Binte Mostafiz et al. 2021).

The vegetation moisture condition was derived from Landsat images using the NDMI (Eq. 10). It is extremely responsive to differences in the canopy water content and is a good indicator of moisture stress and drought conditions. Sufficient water is essential for vegetation growth and productivity; therefore, NDMI plays an important role in understanding the hydrological aspect of vegetation health (Varouchakis et al. 2025).

Apart from the above-mentioned structural and moisture-related features, the vegetation physiological status was evaluated with Sentinel-2 derived red-edge indices. The NDRE (Eq. 11) was used to assess chlorophyll content, photosynthetic efficiency and the health of the canopy. The NDRE is especially useful for identifying very slight stress, which conventional greenness indices are unable to detect in vegetation (Lausch et al. 2018). Likewise, the CI (Eq. 12) was used to evaluate the plant nutrient status and chlorophyll content, which are closely related to the vitality and productivity of plants (Glenn et al. 2008).

The synergy of using NDVI, EVI, SAVI, NDMI, NDRE and CI enabled the evaluation of various aspects of vegetation health such as vegetation vigour, canopy structure, moisture availability, chlorophyll content and nutrient status. These indices were then normalised and aggregated using PCA and overlay weighting to create the VHI. All the indices' related information is given in Table 2.

Data normalisation

To ensure that all vegetation health indicators contribute equally to your final integrated index, they must be brought onto the same scale. Because indicators like NDVI range from −1 to 1, while LST is measured in

Table 2. Calculation of multi-spectral indices

Spectral Index	Purpose	Equation	Bands used from Satellite imagery	Reference
NDVI	Indicates the presence of vegetation cover in the area.	$NDVI = \frac{NIR - Red}{NIR + Red} \ldots\ldots (7)$	Landsat-8/9: NIR = Band 5; Red = Band 4	Vaiphasa et al. 2011
EVI	Accurately measures vegetation greenness, biomass and canopy structure.	$EVI = 2.5 \times \frac{NIR - Red}{NIR + 6 \times Red - 7.5 \times Blue + 1} \quad (8)$	Landsat-8/9: Blue = Band 2; Red = Band 4; NIR = Band 5	X. Huang et al. 2019
SAVI	Corrects index values of low vegetation cover areas.	$SAVI = \frac{NIR - Red}{NIR + Red + 0.5} \times (1 + 0.5) \ldots\ldots (9)$	Landsat-8/9: NIR = Band 5; Red = Band 4	Binte Mostafiz et al. 2021
NDMI	Indicates water content in the vegetation canopy	$NDMI = \frac{NIR - SWIR}{NIR + SWIR} \ldots\ldots (10)$	Landsat-8/9: NIR = Band 5; SWIR = Band 6	Varouchakis et al. 2025
NDRE	Assesses chlorophyll content in plants, nitrogen levels, and canopy health	$NDRE = \frac{NIR - Red\ Edge}{NIR + Red\ Edge} \ldots\ldots (11)$	Sentinel-2: NIR = Band 8; Red Edge = Band 5	Lausch et al. 2018
CI	Indicates plant nitrogen levels	$CI = \frac{NIR}{Green} - 1 \ldots\ldots (12)$	Sentinel-2: NIR = Band 8; Green = Band 3	Glenn et al. 2008

Note: NIR – Near-infrared, SWIR – Short Wave Infrared

degrees Celsius (often ranging from 15 to 45+), raw integration would cause LST to completely skew the results (Cabello-Solorzano et al. 2023). Min-Max normalisation solves this by linearly transforming the data into a standardised, dimensionless scale between 0 and 1. The standard equation for Min-Max normalisation is (Eq. 13):

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (13)$$

where X_{norm} = the normalised, dimensionless value (ranging from 0 to 1), X = the original, raw pixel value of the specific indicator, X_{min} = the minimum value found within that indicator (or its theoretical minimum), and X_{max} = the maximum value found within that indicator (or its theoretical maximum).

For indicators where a lower value means healthier vegetation. This applies to LST because high LST usually correlate with water stress, drought or sparse vegetation. To flip the scale so that low temperatures equal a healthy "1" and high temperatures equal a stressed "0", the inverse formula is used.

Weighting through (PCA)

The PCA is a statistical dimensionality reduction technique that transforms a set of possibly correlated variables into a smaller set of uncorrelated variables called principal components. The first principal component (PC1) captures the maximum amount of variance in the data; the second principal component (PC2) captures the next highest variance orthogonal to PC1 and so on. In the context of vegetation health assessment, PCA is particularly useful because all seven indicators are often correlated with each other. The PCA-based weighting formula is expressed in Eq. 14 (Bro and Smilde 2014):

$$W_i = \frac{W_{raw_i}}{\sum_{i=1}^{n} W_{raw_i}} \qquad (14)$$

where W_i = the weight assigned to the *i* vegetation health indicator, W_{raw_i} = loading (eigenvector coefficient) of indicator i on PC1, and $\sum^{n}_{1=1} W_{raw_i}$ aggregates these raw values across all n vegetation health indicators to establish the total weight baseline.

Overlay mapping

Individuals' vegetation health indicators were combined into a composite VHI by performing a weighted overlay analysis after normalisation and determination of indicator weights using PCA. Weighted overlay is a multi-criterion evaluation

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method that integrates multiple thematic layers according to their relative influence on vegetation health (Tan and Xu 2014). The weights obtained from PCA were used to include NDVI, EVI, SAVI, NDRE, CI, NDMI and LST in the overlay analysis of the normalised layers. The variables whose influence on vegetation health was greater had larger weights, while those with smaller explanatory power had smaller weights. All the normalised raster layers were multiplied by the weights computed from the PCA and then all the raster layers were summed pixel-wise to produce the composite VHI. The conventional VHI is commonly formulated using the vegetation conditions and thermal conditions. The present study develops a PCA-based composite VHI by integrating seven normalised satellite-derived indicators (NDVI, EVI, SAVI, NDMI, NDRE, CI and LST) representing vegetation vigour, moisture status, physiological/chlorophyll condition and thermal stress. Thus, VHI in this study refers specifically to the PCA-weighted composite index developed for Hamirpur District and should not be interpreted as the conventional VCI-TCI formulation.

Results and discussion

Description of multi-spectral indices

The descriptive statistics of the vegetation health indicators show significant improvements in Hamirpur District from 2015 to 2025. LST stands out amongst all the variables as having a significant negative trend (Figs. 3-5). The mean LST decreased from 38.50 °C in 2015 to 35.13 °C in 2020 and further to 32.40 °C in 2025 (Table 3). At the same time, the standard deviation decreased from 2.94 to 2.15, which corresponds to a decrease in the spatial variability of thermal conditions. The decreases in maximum and mean temperatures indicate less thermal stress for vegetation and better environmental conditions.

The vegetation greenness indicators also showed continued improvement throughout the study. The mean NDVI increased from 0.343 in 2015 to 0.422 in 2020 and further to 0.474 in 2025. Likewise, the peak values of NDVI rose to 0.808 from 0.762, indicating higher density and productivity of the vegetation. The upward trend in the mean values shows a general increase in the amount of healthy vegetation cover and

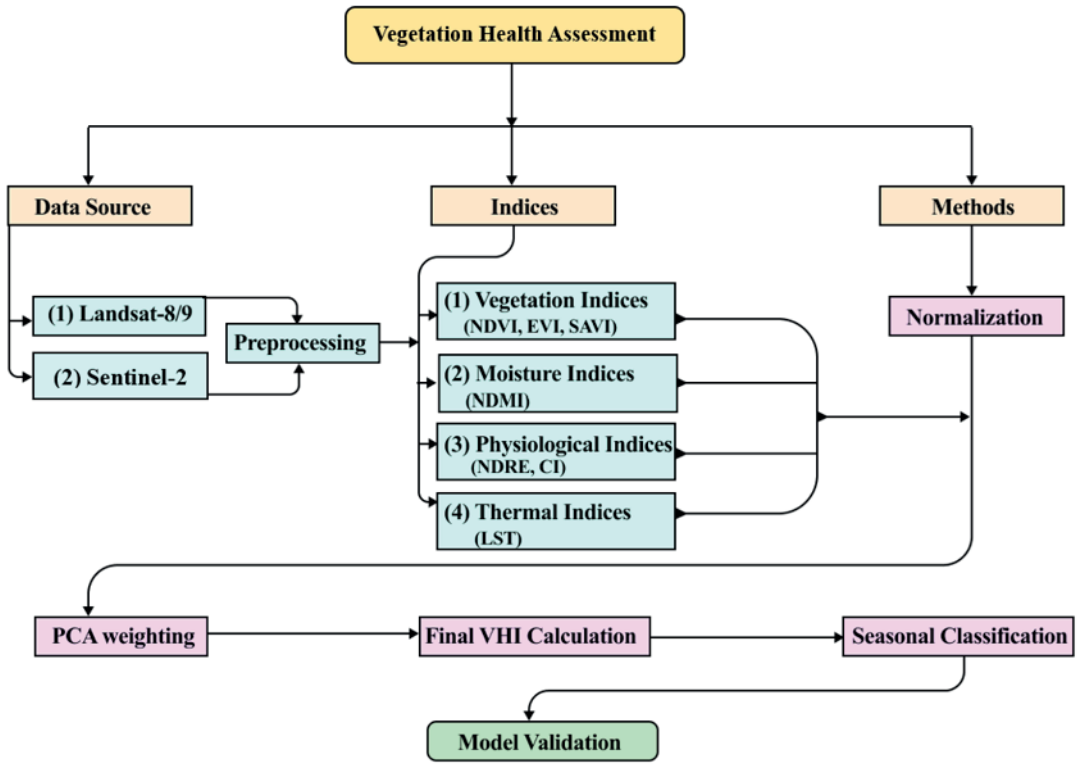


Fig. 2. Research methodology

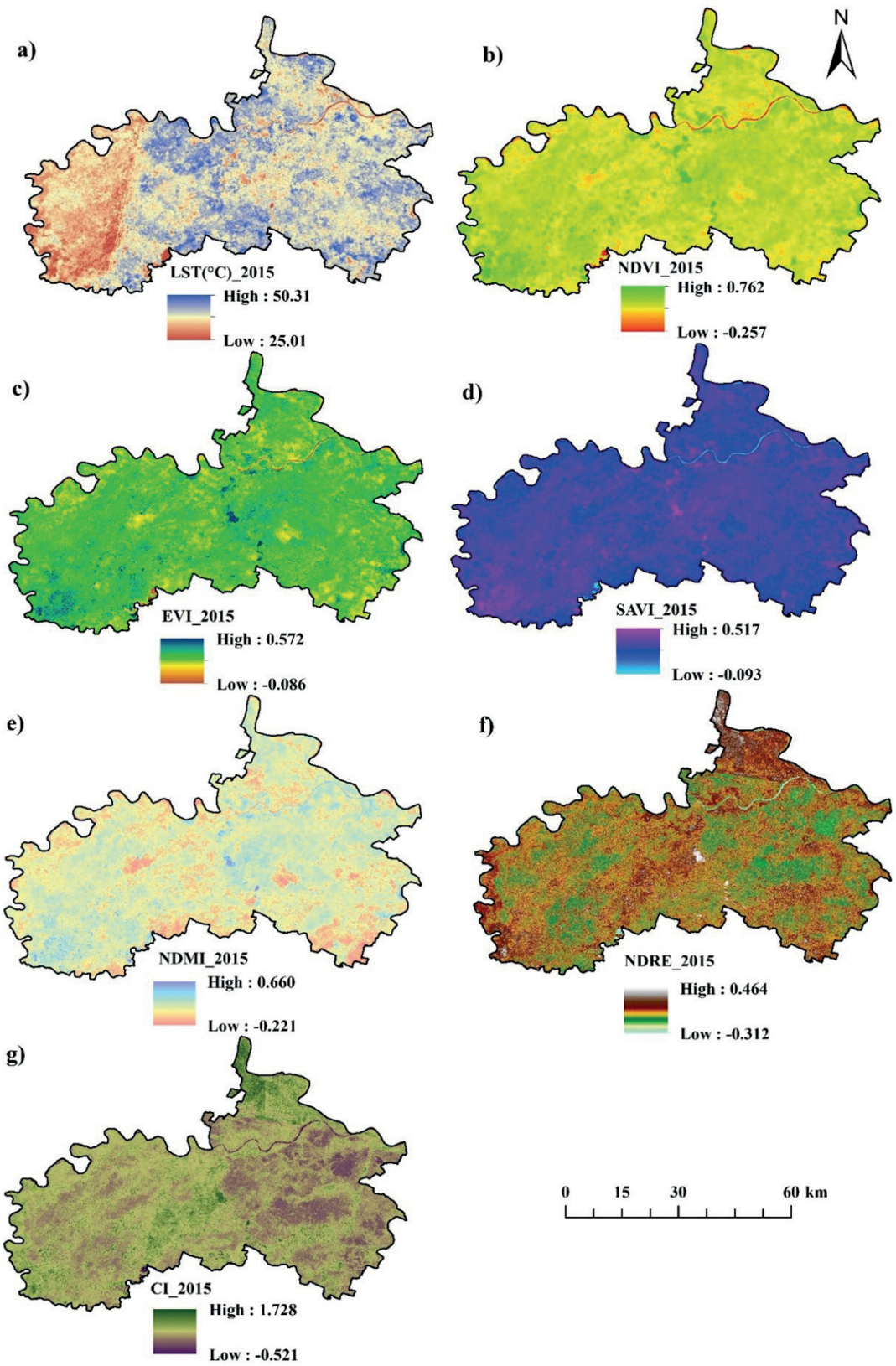


Fig. 3. VHI indicators in the year 2015 (a: LST, b: NDVI, c: EVI, d: SAVI, e: NDMI, f: NDRE and g: CI)

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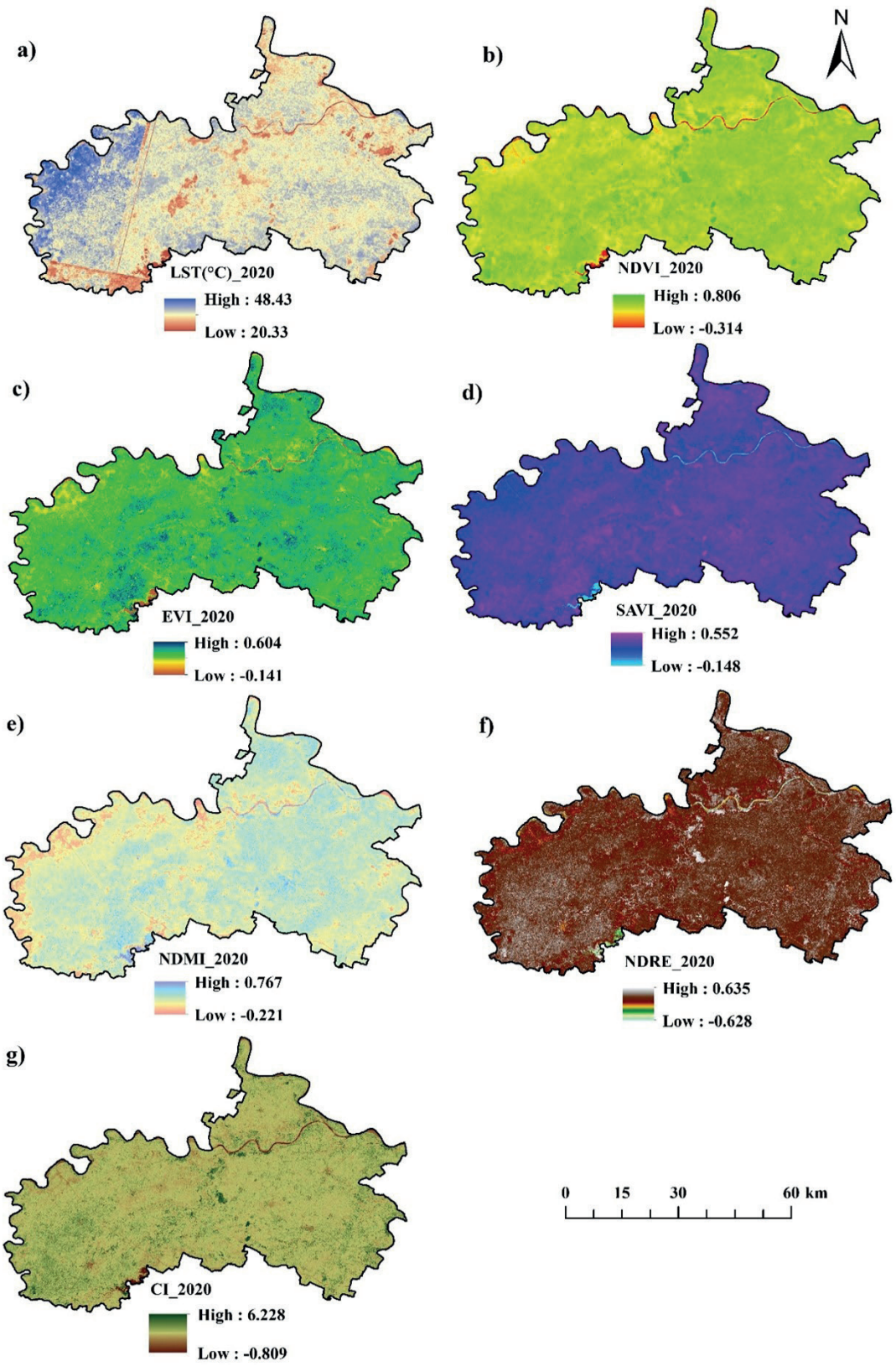


Fig. 4. VHI indicators in the year 2020 (a: LST, b: NDVI, c: EVI, d: SAVI, e: NDMI, f: NDRE and g: CI)

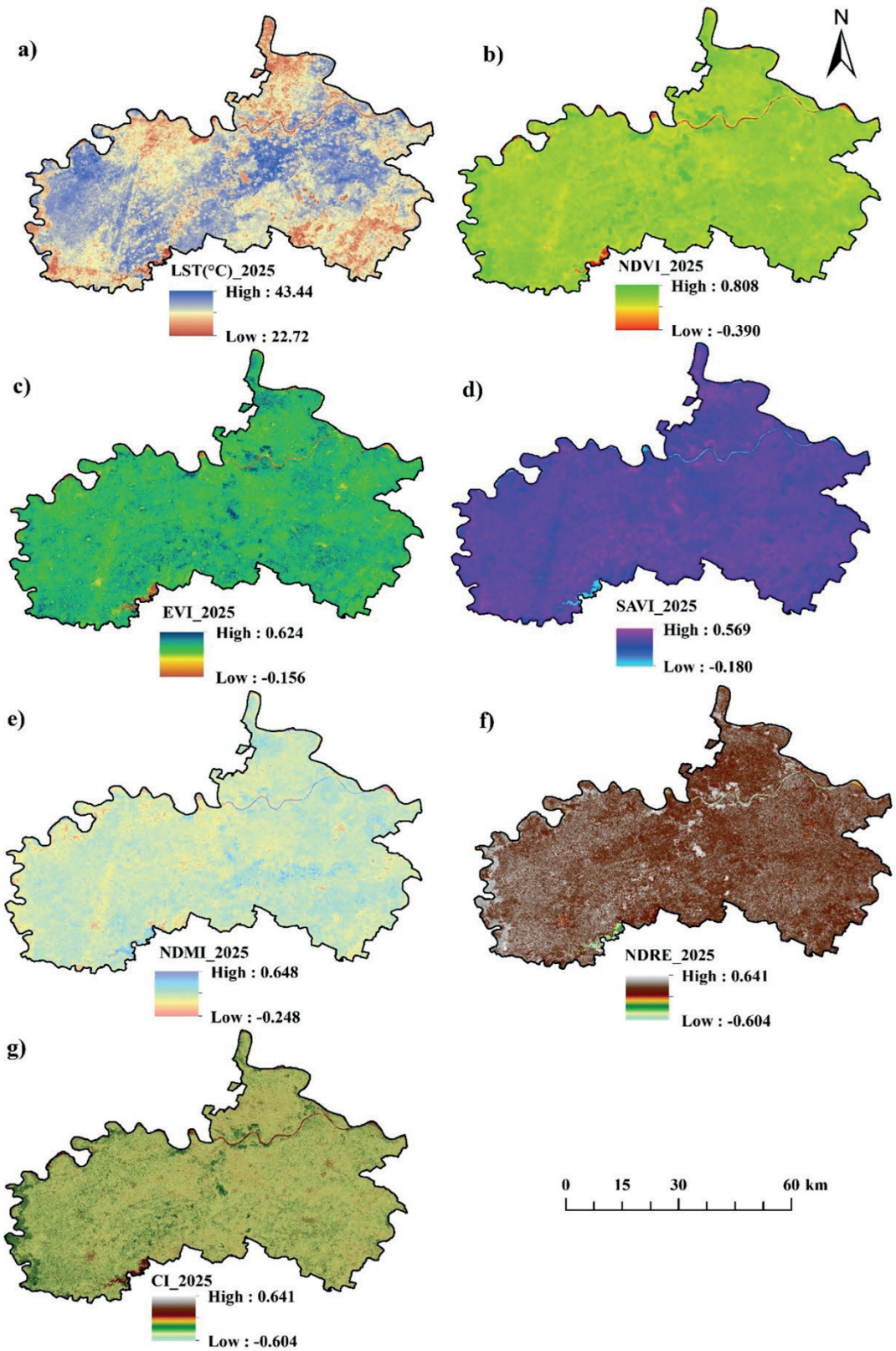


Fig. 5. VHI indicators in the year 2025 (a: LST, b: NDVI, c: EVI, d: SAVI, e: NDMI, f: NDRE and g: CI)

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an increase in photosynthetic activity across the district (Babbar et al. 2021). The relatively low standard deviation indicates that improvements in vegetation were not limited to specific areas but extended on a broader scale throughout the study area.

The same trend was noted in the case of EVI, where the mean value of 0.225 in 2015 jumped to 0.307 in 2025. The greater the EVI, the better the canopy is becoming, more biomass is being added and the vegetation is more productive. The positive trend of EVI further indicates the strength of the observed vegetation recovery, as it is less impacted by atmospheric effects and vegetation saturation than NDVI. Similarly, the mean SAVI rose from 0.226 in 2015 to 0.306 in 2025, which shows that vegetation conditions, even in those areas with low vegetation cover and bare ground, have improved. It is significant to note that these findings are relevant to the semi-arid nature of the terrain, where the soil background effects may impact the results of vegetation assessments (Chacko et al. 2021).

Conditions in other moisture-related areas also improved significantly. The mean NDMI increased from nearly zero (0.006) in 2015 to 0.134 in 2025. The positive trend in the mean and the increased maximum values indicate improved water availability for vegetation and increased canopy moisture. Overall, the increase in NDMI in the later years of the study period suggests improved resilience of vegetation and less of the moisture stress to which the region is prone.

All variables showed differences, but the most significant changes were shown by the chlorophyll-sensitive indicators. The mean NDRE increased from 0.095 in 2015 to 0.242 in 2020 and reached 0.282 in 2025. Likewise, the CI rose from 0.095 to 0.282 over the same period. The increases shown are large and reflect increased chlorophyll concentration, photosynthetic efficiency and better vegetation physiological conditions (Singh et al. 2024a).

PCA weighting of indicators

The PCA results showed that all the vegetation health indicators had positive contributions to PC1, suggesting a high level of association between vegetation vigour, moisture status, chlorophyll content and

Table 3. VHI variables statistics

Variable	Year	Minimum Value	Maximum Value	Mean	Standard Deviation
LST	2015	25.019	50.312	38.499	2.935
	2020	20.333	48.436	35.132	2.713
	2025	22.725	43.445	32.404	2.153
NDVI	2015	-0.257	0.762	0.343	0.087
	2020	-0.314	0.806	0.422	0.093
	2025	-0.390	0.808	0.474	0.093
EVI	2015	-0.086	0.572	0.225	0.055
	2020	-0.141	0.604	0.269	0.060
	2025	-0.156	0.624	0.307	0.062
SAVI	2015	-0.093	0.517	0.226	0.053
	2020	-0.148	0.552	0.270	0.057
	2025	-0.180	0.569	0.306	0.059
NDMI	2015	-0.221	0.006	0.006	0.060
	2020	-0.221	0.767	0.089	0.075
	2025	-0.248	0.648	0.134	0.070
NDRE	2015	-0.312	0.464	0.095	0.055
	2020	-0.628	0.635	0.242	0.088
	2025	-0.604	0.641	0.282	0.096
CI	2015	-0.312	0.464	0.095	0.055
	2020	-0.628	0.635	0.242	0.088
	2025	-0.604	0.641	0.282	0.096

thermal conditions. The first principal component accounted for 86.69% of the total variance, which showed that the selected indicators explained most of the variance related to vegetation health in Hamirpur District (Table 4).

Of all the indicators, NDVI had the highest PCA-derived weight (15.15%), followed closely by NDMI (15.10%). These weights reflect the relative contribution of each indicator to the statistical variance captured by PC1 and should not be interpreted as direct measures of ecological importance. The results indicate that vegetation greenness and canopy moisture contributed substantially to the multivariate variance represented by the composite index in Hamirpur District. The relatively high PCA weight of NDVI reflects its contribution to the variance captured by PC1, while the similar weight of NDMI indicates a comparable statistical contribution of canopy moisture to the composite index.

Other significant contributors to the overall VHI were also NDRE (14.80%), SAVI (14.74%) and EVI (14.59%). The weight of NDRE highlights its relevance for representing canopy physiological condition and chlorophyll concentration. Likewise, the use of SAVI and EVI suggests that vegetation structure, biomass and the response of vegetation to soil are all important considerations for ecosystem condition. Balanced weights for NDVI, SAVI, EVI, NDMI and NDRE indicate that vegetation health in Hamirpur is affected by more than one contributing variable because of the factors affecting vegetation structure, physiology and hydrology.

The CI was 13.45%, and this parameter played an important role in representing plant nutrient status and photosynthetic efficiency. It had a relatively low weight compared to the other two, but its contribution nevertheless highlighted that vegetation vitality and health-related information is valuable from chlorophyll-related characteristics. The inverse or cooling factor of LST was the least weighted variable (12.17%). Although this contribution was relatively small, LST still played a significant role in the index given that the thermal state has a direct impact on evapotranspiration, moisture stress and vegetation productivity.

Final VHI calculation

The VHI developed in this study is a PCA-based composite index that integrates seven indicators representing vegetation vigour, chlorophyll, moisture and thermal stress. While the overall vegetation health remained fairly good from 2015 to 2025, descriptive statistics demonstrate a significant improvement in overall vegetation health conditions over this period, which suggests a decrease in environmental stress and an improvement in ecological conditions (Fig. 6).

The values of VHI range from 0 to 1, with higher values corresponding to healthier vegetation, higher greenness, chlorophyll content, moisture availability and lower thermal stress. In 2015, VHI ranged from 0.035 to 1.000, with a mean of 0.331 and a standard deviation of 0.127 (Table 5). The mean is relatively low, which means many areas of the district were in poor to moderate vegetation health.

In 2020, the mean VHI also rose to 0.543, around 64% higher than 2015. The increase is due to enhanced vegetation vigour, moisture and physiology throughout the district. The standard deviation also

Table 4. PCA weighting of VHI variables

Variables	PC1 Loading	Absolute Loading	PCA Weight	PCA Weight %
NDVI	0.3997	0.3997	0.1514	15.1472
SAVI	0.3890	0.3890	0.1474	14.7402
EVI	0.3850	0.3850	0.1459	14.5910
NDMI	0.3986	0.3986	0.1510	15.1044
NDRE	0.3905	0.3905	0.1479	14.7970
CI green	0.3549	0.3549	0.1344	13.4492
LST cool	0.3212	0.3212	0.1217	12.1706
PC1 explained variance	**0.8669**			

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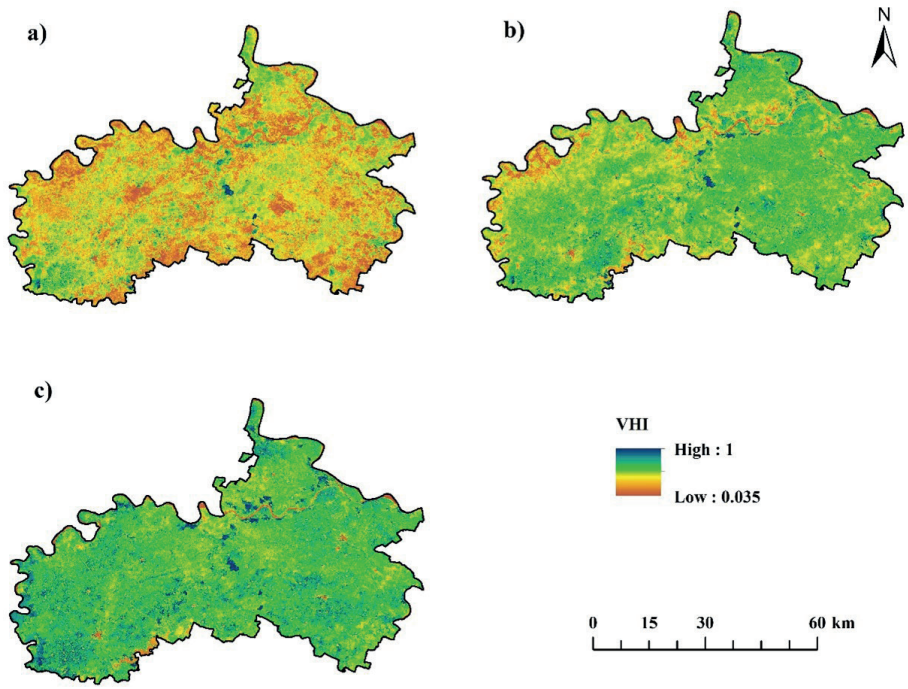


Fig. 6. Final VHI (a: 2015, b: 2020 and c: 2025)

Table 5. VHI Statistics

Variable	Year	Minimum Value	Maximum Value	Mean	Standard Deviation
VHI	2015	0.035	1.000	0.331	0.127
	2020	0.000	1.000	0.543	0.161
	2025	0.000	1.000	0.633	0.151

increased from 0.127 to 0.161, suggesting increased spatial variation in the health of vegetation and that the improvements were not uniform throughout the district.

This positive trend continued through 2025, when the mean VHI was 0.633, which is approximately 91% higher than in 2015. The standard deviation was slightly lower at 0.151, which showed more evenness in vegetation health than in 2020, with a standard deviation of 0.161, showing that spatial variability in vegetation health across the landscape was reduced.

High VHI values (near 1.000) persisted throughout the study period, showing the occurrence of highly healthy vegetation areas. The significant rise in mean VHI, however, indicates a significant growth of healthy vegetation, not just within localised areas. While minimum values remained low in both years 2020 and 2025, these are relatively small areas of stressed or sparsely vegetated conditions as compared to the growth in the area of healthy vegetation classes.

VHI change detection

The VHI results at the district level suggest significant enhancement in vegetation health in Hamirpur District from 2015 to 2025 (Table 6; Fig. 7). Transitions observed indicate positive ecological change, with an increase in better vegetation categories and a decrease in poorer categories.

The Very Poor category exhibited the greatest decline, decreasing from 603.90 km² in 2015 to 395.91 km² in 2020 and 247.82 km² in 2025. This loss corresponds to a significant decrease in the areas of severely stressed vegetation and their conversion into healthier

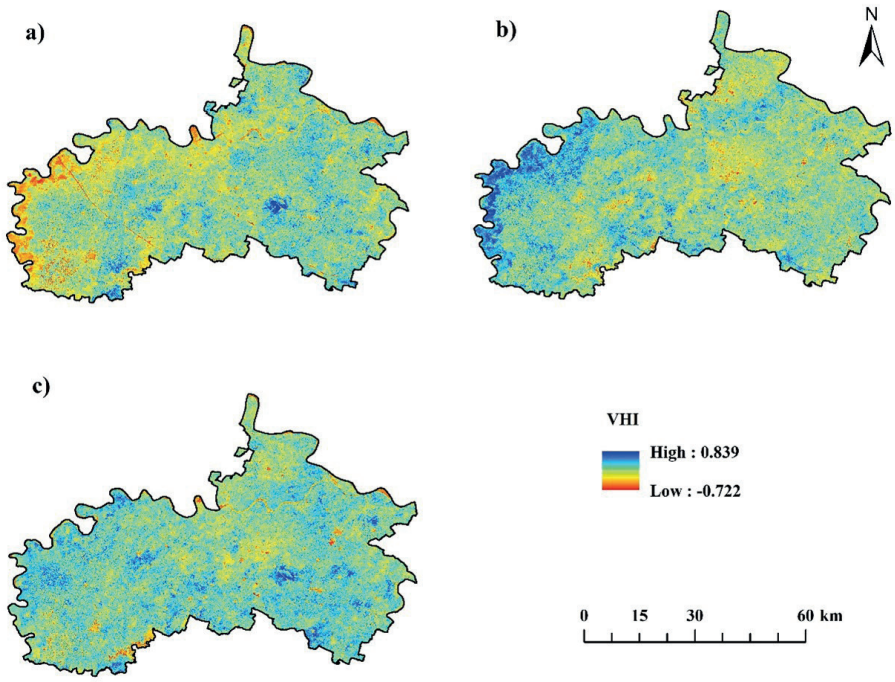


Fig. 7. VHI change analysis (a: 2015–2020, b: 2020–25 and c: 2015–2025)

Table 6. Category-wise change in VHI

Category	2015 (km^2)	2020 (km^2)	2025 (km^2)	Change 2015-20 (km^2)	Change 2020-25 (km^2)	Change 2015-25 (km^2)	Change 2015-20 (%)	Change 2020-25 (%)	Change 2015-25 (%)
Very Poor	603.90	395.91	247.82	-207.99	-148.09	-356.08	-34.44	-37.40	-58.96
Poor	1500.90	1355.20	1136.97	-145.70	-218.23	-363.93	-9.71	-16.10	-24.25
Moderate	1463.22	1208.62	1027.80	-254.60	-180.82	-435.42	-17.40	-14.96	-29.76
Healthy	417.96	825.24	1151.91	407.28	326.67	733.95	97.44	39.58	175.60
Very Healthy	135.92	336.93	557.40	201.01	220.47	421.48	147.89	65.43	310.09
Total	**4121.9**	**4121.9**	**4121.9**	-	-	-	-	-	-

vegetation classes (356.08 km^2 or 58.96%). Similarly, the Poor category declined steadily from 1500.90 km^2 in 2015 to 1136.97 km^2 in 2025, recording a net reduction of 363.93 km^2 (24.25%). This is a small improvement on the Vegetation Condition Very Poor category, but it does indicate significant improvement in vegetation conditions throughout the district. The Moderate category also decreased from 1463.22 km^2 in 2015 to 1027.80 km^2 in 2025, a reduction of 435.42 km^2 (29.76%). The intermediate vegetation condition areas were seen to increase in healthier classes in this trend. The overall reduction in the Very Poor, Poor and Moderate categories verifies that the improvement was not just in certain areas but was seen throughout the district.

The Healthy category, on the other hand, experienced phenomenal growth. Its area increased from 417.96 km^2 in 2015 to 825.24 km^2 in 2020 and 1151.91 km^2 in 2025. This net gain of 733.95 km^2 reflects significant enhancements in vegetation vigour, available moisture and ecological health. The biggest increase was in the Very Healthy category. Its area expanded from 135.92 km^2 in 2015 to 557.40 km^2 in 2025, an increase of 421.48 km^2 or 310.09%. This expansion is a result of the spread of vegetation under optimal health conditions with better greenness, chlorophyll content, moisture conditions and lower thermal stress.

The VHI transition reveals a definite shift from degraded and stressed vegetation to healthy and more resilient vegetation. The overall negative change (–1,155.43 km^2) in the Very Poor, Poor and Moderate categories was mirrored by positive change (+1,155.43 km^2) in the Healthy and Very Healthy categories.

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Seasonal VHI variation

The seasonal trends of VHI in the Hamirpur District in 2015–25 show considerable temporal variability in the vegetation health at different time intervals, which relates to climatic conditions, moisture availability and vegetation growth patterns (Table 7). Overall, there was a general increase in the health of vegetation in all seasons, but to differing extents.

Much seasonal variation occurred in vegetation health in 2015. Summer had the highest VHI (0.609), which was healthy, and winter was Fair (VHI=0.536). Moderate vegetation stress was reported for both monsoon (0.488) and post-monsoon (0.290) seasons. The low post-monsoon VHI indicated moisture stress and senescence of vegetation and environmental pressure following the rains.

Seasonal vegetation health was significantly improved by 2020. However, on the seasonal scale, the VHI was highest during the winter (0.618) and into the Healthy category and remained in the Fair category during summer (0.508), monsoon (0.566) and post-monsoon (0.481). The highest gain was seen during the post-monsoon season, when VHI went from 0.290 to 0.481, representing a significant decrease in vegetation stress. Lower seasonal variations also indicated a more uniform state of vegetation throughout the year.

The year 2025 had the highest seasonal VHI values. The highest VHI (0.655) was found during the winter and the lowest VHI (0.631) was observed during the summer, both of which are considered in the Healthy condition. Post-monsoon VHI (0.632) was observed as a Healthy condition. The VHI was 0.507 during the monsoon season and was still in the Fair range. A significant improvement was noted for the post-monsoon season, moving from Moderate stress in 2015 to Healthy in 2025, which suggests better moisture availability, greater stress potential for the vegetation, and lower environmental stress.

The time series comparison of the vegetation health trend reveals that the highest vegetation health is observed in winter, rising from 0.536 in 2015 to 0.655 in 2025. This could be related to favourable conditions of temperature, reduced evapotranspiration and soil moisture. The slight increase in vegetation health from 0.609 to 0.631 in the summer also indicates increased tolerance to heat stress. The post-monsoon season showed the greatest relative improvement, with an increase in VHI by around 118% from 2015 to 2025, indicating better recovery of vegetation and increased stability of the ecosystems.

Model validation

The reliability of VHI has been tested and confirmed by comparing the results with the independent statistics for Hamirpur District (Table 8). The validation results show good correlation between the changes in VHI and related changes in environmental and agricultural conditions. Over the study period, annual rainfall was also significantly high, from 530.28 mm to 851.15 mm, which confirms that moisture availability was high and favourable conditions existed for vegetation growth. At the same time, the land that was under natural vegetation increased from 251.57 km² to 493.32 km², and fallow land fell by 110.07 km², reflecting showing conversion from fallow to natural vegetated or Net

Table 7. Seasonal VHI

Year	Season	VHI Value	VHI Class	Label
2015	Winter	0.536	3	Fair
	Summer	0.609	4	Healthy
	Monsoon	0.488	3	Fair
	Post Monsoon	0.29	2	Moderate stress
2020	Winter	0.618	4	Healthy
	Summer	0.508	3	Fair
	Monsoon	0.566	3	Fair
	Post Monsoon	0.481	3	Fair
2025	Winter	0.655	4	Healthy
	Summer	0.631	4	Healthy
	Monsoon	0.507	3	Fair
	Post Monsoon	0.632	4	Healthy

Table 8. Data for VHI model validation

No.	Variable Name	2015	2024	Difference
1.	Rainfall	530.28 mm	851.15 mm (2025)	+320.87 mm
	Land Use Pattern (Area in km²)			
2.	Natural Vegetated Area	251.57	493.32	+241.57
3.	Fallow Land	185.83	75.76	-110.07
	Agricultural Statistics			
4.	Gross Irrigated Area (Area in km²)	1522.30	1664.61	+142.31
5.	Area sown more than once (Area in km²)	707.77	1073.22	+365.45
6.	Tube Wells (Number)	16117	17539	+1422
7.	Solar Tubewells (Number)	00	246	+246

Source: 1. https://www.jjm.up.gov.in/groundWater/Rain_fall_Data_ON_Map; 2. Directorate of Economics and Statistics U.P. https://updes.up.nic.in; 3. https://updes.up.nic.in/spideradmin/Hpage1.jsp

Sown Area cultivated landthe restoration of vegetation. The increase in the gross irrigated area (+142.31 km²) and in the number of times the land was sown more than once (+365.45 km²) further corroborate the VHI results, indicating a higher agricultural intensity and land productivity. Expansion of irrigation facilities: 1422 additional tube wells and introduction of 246 solar-powered tube wells likely benefited access to water and lessened moisture stress on the cultivated landscapes. The positive changes are in close accordance with the observed improvement from 0.331 in 2015 to 0.633 in 2025 for the mean VHI, as well as the increase in area categorised as exhibiting the number of Hhealthy or and Very Healthy vegetation. The agreement between the satellite-derived VHI trends and the independent environmental and agricultural statistics provides indirect support for the observed temporal changes in vegetation conditions. However, these secondary datasets do not constitute direct spatial validation of vegetation health at the pixel or field level. Therefore, the validation should be interpreted as corroborative rather than definitive. Future studies should strengthen validation through field-based observations, plot-level vegetation measurements, or independent vegetation products and datasets to assess the spatial accuracy and generalisability of the VHI.

Limitations and future scope

This study has several limitations. First, validation of the PCA-based VHI relied mainly on secondary environmental and agricultural statistics, which provide indirect temporal support but do not directly validate pixel-level vegetation health conditions. Second, PCA-derived weights are data-dependent and were calculated specifically for Hamirpur District; therefore, direct transfer to other Bundelkhand districts or ecological settings may not be appropriate. Third, satellite-derived indicators may not fully capture field-level vegetation characteristics, species composition, management practices or localised ecological conditions. Future research should incorporate systematic field observations, plot-level vegetation measurements and independent vegetation products to strengthen spatial validation. Multi-source datasets, including higher-resolution satellite imagery, climatic variables, soil moisture, groundwater and land-use information, could improve interpretation of vegetation dynamics. Recalibrating PCA weights for each study area and conducting cross-district validation would improve framework robustness and transferability. Longer time series and machine-learning approaches could additionally support prediction and early detection of vegetation stress.

Conclusion

The purpose of this study was to develop a comprehensive PCA-based VHI by integrating seven complementary satellite-derived indicators. The methodological contribution of the study lies in combining PCA-based objective weighting with GIS-based weighted overlay to integrate these complementary indicators into a single spatially explicit

vegetation health framework. This approach reduces dependence on a single vegetation index and provides a multidimensional assessment of vegetation conditions in the semi-arid environment of Hamirpur District. This finding shows a significant increase in vegetation health in Hamirpur District, highlighting improvements in ecosystem functioning and resilience over time. The statistical analysis showed a uniform increase in productivity, moisture availability and chlorophyll content, along with a significant decrease in LST. There was a significant improvement in overall vegetation condition from 0.331 (2015) to 0.633 (2025) for the mean VHI. This positive shift was also reflected in the analysis by vegetation health category, with significant improvements in the percentages of Healthy and Very Healthy vegetation health classes and significant declines in Very Poor, Poor and Moderate vegetation health classes.

Vegetation health was assessed seasonally and showed an improvement in vegetation health for all seasons, with winter and summer always having the highest VHI value. The significant improvement of the post-monsoon vegetation situation was of particular interest, with conditions shifting from moderate stress to healthy conditions by 2025. The results indicate increased vegetation resistance, better moisture-holding capacity and greater ecosystem stability in the annual growth pattern.

Policy implications

The results of this study hold significant implications for environmental management, adaptation to climate change and sustainable development planning in semi-arid regions. The VHI framework can be used to support district-level decision-making and to identify district areas in need of ecological intervention and the state of environmental stress. VHI maps can be used for environmental monitoring systems to identify vegetation degradation hotspots and focus ecological restoration efforts. They are good outputs for afforestation, watershed development and land rehabilitation programmes. The methodology can additionally be utilised for observing environmental sustainability, ecosystem recovery objectives and climate resilience plans at district and state level in a geospatial decision-support framework. Moreover, the framework is low-cost, using freely available satellite data.

Societal implications

The environmental, social and economic benefits of improved vegetation health are significant. Vegetation is healthy, mostly in rural areas, providing agricultural production, animal husbandry, groundwater recharge and vital ecosystem services. Better vegetation cover will lead to better environmental security and drought/land-degradation resistance, as well as providing better soil conservation. The presence of sparse vegetation results in high surface temperatures and lack of moisture, whereas higher vegetation presence results in favourable microclimatic conditions. The resulting benefits contribute to rural communities' sustainability, food security and climate resilience. Also, healthier ecosystems offer long-term economic benefits in the form of sustainable materials on demand and lower expenses of environmental damage and revitalisation.

Recommendations

The results indicate that a thorough and preventive approach to vegetation management is required in Hamirpur District. Vegetation conditions are generally better than they were in 2015, but there are large areas of Very Poor and Poor vegetation classes which do need targeted ecological interventions. Afforestation, assisted natural regeneration, agroforestry promotion and rehabilitation of degraded lands should be prioritised to improve vegetation cover and resiliency of the ecosystem. Water resource management should be incorporated in environmental planning by introducing the development of watersheds, water harvesting systems, establishment of farm ponds and development of groundwater recharge systems for better soil moisture and maintenance of vegetation growth. This is especially crucial in semi-arid areas like Hamirpur, where water is of key importance to avoid degradation of vegetation. The next step would be to incorporate vegetation health metrics with the variability of rainfall, the state of groundwater, land-use change, and socio-economic factors in order to better understand vegetation dynamics. Using cutting-edge Machine Learning and Geo-AI methods could further enhance predictive assessments and guide evidence-based planning. Moreover, the PCA-based VHI approach developed in this study provides a framework that may be applied to other districts of the Bundelkhand region; however, the PCA-derived weights are data-dependent

and may vary according to local ecological, climatic and land-cover conditions. Therefore, application to other districts should involve recalculation and validation of the PCA weights using locally representative data rather than directly transferring the weights obtained for Hamirpur District.

Disclosure statement

No potential conflict of interest was reported by the authors.

Author contributions

Study design: AKD; data collection: TR, AKD; statistical analysis: TR, AKD; manuscript preparation: AKD, AV; literature review: AKD, AV.

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