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Mapping urban stress and green depletion in Shimla using remote sensing: A step towards sustainable urban future

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Abstract
The tracking of vegetation dynamics and urban growth is necessary for ecologically sound environmental planning, especially in ecologically vulnerable areas such as Himachal Pradesh. This paper provides a detailed examination of the seasonal correspondence between NDVI (normalized difference vegetation index) and NDBI (normalized difference Built-up index**)** from 2019 to 2024 based on Sentinel-2 imagery, chosen for its high spatial resolution and regular availability from 2019. A total of 50,000 spatially distributed but fixed points were analyzed across all districts of Himachal Pradesh. Karl Pearson's correlation coefficient was calculated season-wise by Python to reflect the relationship between NDVI and NDBI, which indicated a persistent negative correlation pattern, mainly in urbanizing areas. Time series and trend analysis were undertaken to evaluate long-term vegetation and built-up pattern changes, with a linear regression model used to project trends up to 2030. Findings show an evident seasonally related reduction in vegetation cover that parallels urban growth in major districts. Further, a heatmap of correlations was created to display spatial variation in the relationship between NDVI-NDBI, emphasizing ecological hotspots as well as zones of significant transition. This research offers policy-relevant findings for policymakers and urban planners in that it maps out regions most impacted by anthropogenic pressure and climatic variability in the Western Himalayan environment.

Keywords: Urban expansion, vegetation dynamics, Karl Pearson correlation, linear regression, trend forecasting, remote sensing, seasonal analysis, ecological stress, correlation heatmap, python, normalized difference vegetation index, environmental sustainability, normalized difference built-up index

1. Introduction

Himachal Pradesh, a north Indian mountain state, is experiencing a process of accelerated land use modification as a result of intensified urbanization and developmental pressure. Historically famous for dense forest cover, high biodiversity, and sensitive ecosystems, the Western Himalayan region increasingly suffers from increased environmental pressure in the form of expanding built-up lands, infrastructure, and altered land cover. These changes have immediate implications for ecological equilibrium, soil stability, and climate sensitivity in the Western Himalayas (Mehra & Swain, 2025) [7]. To evaluate these changes, this research examined the seasonal and temporal correlation between the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI) for the whole state from 2019 to 2024. Utilizing high-resolution Sentinel-2 satellite imagery and Python-based analytical tools, we calculate seasonal correlations, create heatmaps, and employ time series and trend analysis to identify spatial patterns and predict land cover changes. The aim is to emphasize regions of ecological tension and urban growth in order to facilitate data-driven planning in this ecologically fragile area.

The distribution of urban ecological stress in Himachal Pradesh, a rapidly urbanizing mountain state in North India, is evaluated in this study using a geospatial approach. Two commonly used remote sensing indices, NDVI (Normalized Difference Vegetation Index) and NDBI (Normalized Difference Built-up Index), were calculated seasonally using high-resolution Sentinel-2 satellite imagery from 2019 to 2024 in order to assess the health of the vegetation and the growth of built-up in a variety of landscapes. Consistent, cloud-free, high-resolution Sentinel-2 data became consistently available for the region only after 2019, which is reflected in the chosen time period. The study maps the shifting equilibrium between natural vegetation and impervious surfaces by comparing NDVI and NDBI trends, highlighting regions experiencing growing ecological stress as a result of urbanization. This method facilitates data-driven strategies for sustainable regional planning and allows for a thorough understanding of land surface transformation in the Western Himalayas. Since urban ecological studies have long used NDVI and NDBI as complementary indicators, they are suitable instruments for tracking the environmental effects of urbanization in hilly, sensitive areas (Ouma *et al*., 2021) [8].

Remote Sensing (RS) and geospatial technologies are now critical instruments in the quest for environmental sustainability and the promotion of green economy projects. They enable systematic observation, measurement, and analysis of Earth's surface characteristics over large spatial areas and long temporal durations. They offer timely, affordable, and repeatable methods of monitoring environmental change, particularly in areas of rapid urbanization and ecological changes (Grover & Kaur, 2024; Susaki *et al*., 2014) [2, 10]. Remote sensing is a crucial tool for tracking changes in land use and cover in both urban and rural areas of Himachal Pradesh. Traditional field surveys can be difficult and resource-intensive due to the state's intricate mountainous terrain and ecological sensitivity. (Robinson *et al*., 2017; Vaid & Pathania, 2024) [9, 11].

Among different remote sensing-based indicators, the Normalized Difference Vegetation Index (NDVI) is a powerful tool for vegetation health and density. It is chlorophyll sensitive and able to capture greenness levels over a range of land covers (Li *et al*., 2021) [5]. The Normalized Difference Built-up Index (NDBI) is employed for identifying built-up features and assisting in mapping the extent of urban infrastructure. These two indices combined, when examined simultaneously, provide a measure of the competing forces between natural and developed landforms (Guha *et al*., 2018; Zha *et al*., 2003) [3, 14]. Aside from spatial mapping, this work also includes a correlation analysis of NDVI and NDBI to statistically assess the relationship between vegetation cover and built-up intensity in the urban landscape. This kind of analytical technique is essential for quantifying the extent to which urban growth is affecting green spaces (Cetin *et al*., 2024) [1]. A seasonal correlation between NDVI and NDBI was carried out throughout Himachal Pradesh using 50,000 randomly chosen sample points in order to further this analysis. A thorough analysis of the temporal and spatial patterns in urban growth and vegetation loss across different climatic zones and altitudinal gradients was made possible by this extensive dataset. Python was used for the correlation analysis and data processing, enabling statistical computation and effective handling of sizable raster datasets.

In this study, a hybrid remote sensing approach was adopted to assess the spatiotemporal relationship between vegetation cover and urban expansion in Himachal Pradesh. High-resolution Sentinel-2 imagery (2019-2024) was utilized to compute seasonal correlation between the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI), enabling precise pattern detection and vegetation-urban stress mapping at a fine scale. However, due to the limited temporal availability of Sentinel-2 data, Landsat 8 level-2 imagery (2014-2024) was employed to derive long-term seasonal trend maps for NDVI and annual map for NDBI. The use of Landsat ensured consistent, decade-long time series analysis, while the Sentinel-based correlation analysis provided high spatial detail for recent years. This integrated approach leverages the strengths of both datasets, enhancing the overall robustness of the spatiotemporal analysis.

An increasing inverse relationship between vegetation cover and built-up expansion throughout Himachal Pradesh was indicated by the analysis, which showed a steadily growing negative correlation between NDVI and NDBI between 2019 and 2024. This pattern demonstrates how, over time, natural vegetation is gradually being replaced by urban development. Significant temporal variations were found when the seasonal analysis was broken down into three categories: spring (March-May), summer (June-August), and autumn (September-November). The autumn season showed the strongest negative correlation, indicating that this time of year is the most ecologically stressed probably as a result of cumulative seasonal vegetation loss, dry weather, and continuous urbanization. The correlations between spring and summer were relatively moderately negative, with spring representing a partial recovery of vegetation following winter and summer representing a brief period of greenery. These findings are further supported and visually validated by NDVI and NDBI trend maps generated from Landsat 8 imagery (2014-2024), which clearly depict areas of long-term vegetation decline coinciding with urban expansion zones (Jaswal & Thakur, 2023) [4].

Finally, the research produces spatially explicit, evidence-based insights to guide various aspects of sustainable urban development. These involve the selection of degraded or high-stress areas for focusing urban greening, planning green infrastructure strategies that incorporate natural elements into urban form, and facilitating nature-based solutions that correspond to larger climate resilience agendas. By connecting satellite-derived indicators to local-scale planning requirements, this study adds to the principles of a green economy supporting ecologically friendly, resource-efficient, and socially inclusive urban development.

2. Methodology

2.1 Study area

Himachal Pradesh is a mountainous state in northern India's western Himalayas that covers an area of about 55,673 km² and lies between latitudes 30°22′N and 33°12′N and longitudes 75°45′E and 79°04′E. From low Shivalik foothills (~350 m) to high-altitude regions above 7,000 m, the region's complicated topography results in a variety of climatic zones and vegetation types. Demographically, Himachal Pradesh has a population of approximately 6.8 million (Census 2011, projected to be over 7.9 million by 2024), with a rural majority and a growing urban footprint concentrated in hill towns and valley settlements The state's physiography is divided into four primary zones: the outer Himalayas (Shivaliks), the lesser Himalayas, the greater Himalayas, and the Trans-Himalayan zone, each influencing the region's microclimates, vegetation types, and land use patterns. As per Forest Survey of India Report 2021, Himachal Pradesh has 15,443 sq km (27.73%) of its area under forest cover. Because of its diverse topography and climate, the Himachal Pradesh's forests are home to a wide range of flora and fauna, making them rich in biodiversity. Chil, Deodar, Kail, Fir, Spruce, Oak, Khairi, Sal, Bamboo, and other broad-leaved species are found in these forests. These forests are categorized into tropical, sub-tropical, temperate, and alpine types, supporting rich biodiversity and playing a key role in carbon sequestration and watershed regulation (Forest Survey of India, 2023).

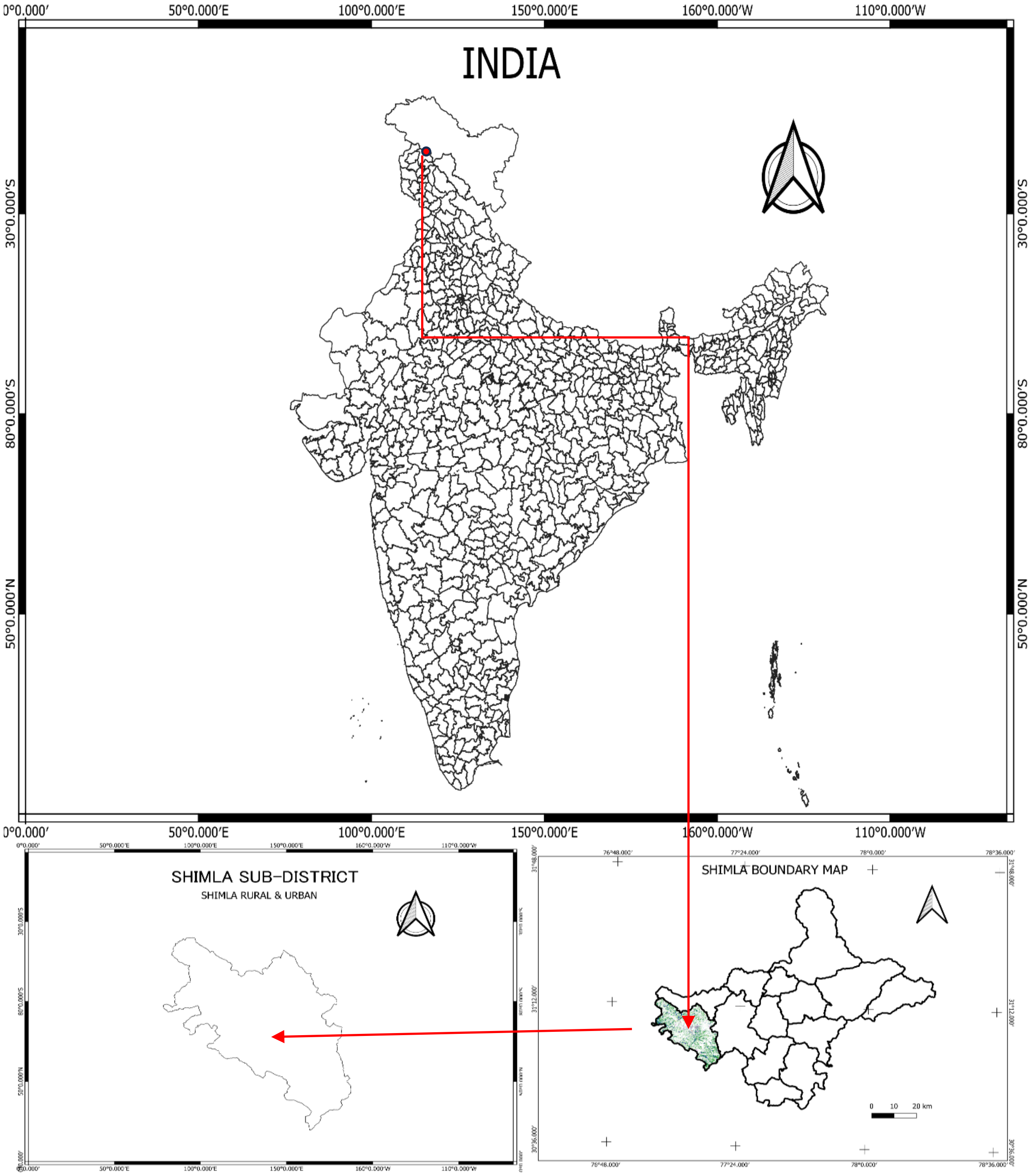

Fig 1: Location maps of the study area

2.2 Preprocessing of image

To guarantee high radiometric and geometric consistency across all temporal datasets, Sentinel-2 Level-2A imagery (2019-2024) and Landsat 8 level-2 data (2014-2024) were used for this study. For spring (March-May), summer (June-August), and autumn (September-November), cloud-free imagery was chosen seasonally, excluding monsoon months because of high cloud cover and erratic reflectance levels. The first step in preprocessing was atmospheric correction, which was already used in Level-2A Sentinel and Landsat Surface Reflectance products. Next, clouds and shadows were masked using the pixel quality (QA_PIXEL) band for Landsat 8 and the QA60 band for Sentinel-2. To guarantee spatial consistency, all images were cropped to the Himachal Pradesh border using a high-resolution administrative shapefile. To lessen the effect of outliers and transient anomalies, seasonal image composites were created using median pixel values. The preprocessed datasets that were produced offered a reliable and consistent foundation for additional correlation analysis and trend identification over the chosen time frame.

2.2 Extracting NDVI value

NDVI was calculated using the formula given below from

Sentinel-2 (Bands 8 and 4) for 2019-2024 and Landsat 8 (Bands 5 and 4) for 2014-2024. Seasonal composites for spring, summer, and autumn were generated after masking clouds and shadows. The following formula was applied:

$$NDVI = (NIR - Red) / (NIR + Red) \quad (1)$$

where:
NDVI = Normalized Difference Vegetation Index
NIR = Near Infrared Band
Red = Red Band
Healthy vegetation scatters more near-infrared and less red light, generating higher NDVI values. To maintain consistency in all indices (NDVI and NDBI) was kept in the full range from -1 to +1. This consistent scaling enabled precise comparison and visualization, picking up subtle differences in vegetation even in mixed or transitional land cover areas.

2.3 Extracting NDBI value

NDBI (Normalized Difference Built-up Index) was employed to identify built-up areas in the Himachal Pradesh. It operates by comparing reflectance between shortwave infrared (SWIR) and near-infrared (NIR) bands. Built-up surfaces tend to reflect more SWIR and less NIR, thus making the index efficient to identify urban sprawl. The formula employed was:

$$NDBI = (SWIR - NIR) / (SWIR + NIR) \quad (2)$$

where:
NDBI = Normalized Difference Built-up Index
SWIR = Shortwave Infrared
NIR = Near Infrared Band
NDBI was computed using the formula given above, utilizing Sentinel-2 Bands 11 (SWIR) and 8 (NIR) for 2019-2024, and Landsat 8 Bands 6 and 5 for 2014-2024. Seasonal composites were prepared for spring, summer, and autumn after cloud and shadow masking. NDBI values were extracted for the same 50,000 fixed random points to analyze urban expansion and correlate with NDVI values.

2.4 Correlation analysis

Sentinel satellite imagery was used in QGIS to analyze the relationship between vegetation cover and urban development in Shimla sub-district. NDVI and NDBI rasters were first generated using the raster calculator. These rasters were then converted into point layers so that each pixel had a corresponding geographic point with its NDVI or NDBI value as an attribute. Using Python, the NDVI and NDBI values were merged into a single point layer using geospatial libraries such as geopandas and pandas. This created an attribute table containing paired NDVI and NDBI values for each pixel. The statistical relationship between the values was then analyzed by calculating Pearson's correlation coefficient using Python's scipy.stats.pearsonr function. Pearson’s correlation coefficient (r) measures the strength and direction of the linear relationship between two variables. It is calculated using the formula:

$$r = \Sigma [(X - \bar{X}) (Y - \bar{Y})] / \sqrt{[\Sigma (X - \bar{X})^2 \times \Sigma (Y - \bar{Y})^2]} \quad (3)$$

Where X and Y are the variables (NDVI and NDBI), and $\bar{X}$ and $\bar{Y}$ are their respective means. The result ranges from -1 to +1. A negative value indicates an inverse relationship meaning, as NDBI increases, NDVI decreases. This suggests that urban expansion is linked to vegetation loss. The method offered a clear, pixel-wise understanding of urban stress on green areas.

2.5 Extracting VBEI value and zonation mapping

Vegetation-Built-up Environment Index (VBEI) was derived from Sentinel satellite images in QGIS to estimate the equilibrium between green cover and built-up cover. This study employed the raster calculator to create the VBEI layer by mixing NDVI and NDBI based on the specified formula. After creating the VBEI raster, reclassification of values into interpretable zones like low, moderate, and high stress were carried out. This recoding facilitated visualization of spots where vegetation is under stress because of urbanization. Through the 'symbology' settings and classification tools, a zonation map was created that distinctly showed spatial patterns in the study area. The map facilitated easy identification of areas of urban stress hotspots and assisted in further correlation and land use analysis. The raster calculator was used to generate the VBEI raster layer based on the following formula:

$$VBEI = (NDBI - NDVI) / (NDBI + NDVI) \quad (4)$$

where:
NDBI = Normalized Difference Built-up Index
NDVI = Normalized Difference Vegetation Index

3. Results and Discussion

3.1 Results of vegetation index

This study analyzed NDVI values and helped in reclassification of study area into four-classes as shown in Table 1.

Table 1: Classification of vegetation depending upon NDVI range

Class	NDVI range	Land cover description
Class 1: Non-vegetation	< 0.2	Water, roads, built-up areas
Class 2: Low vegetation	0.2 - 0.4	Grasslands, dry fields
Class 3: Moderate vegetation	0.4 - 0.5	Cropland, plantations
Class 4: High vegetation	> 0.5	Dense forest, lush green cover

This helped us in understanding the vegetation patterns more clearly. Using NDVI has the benefit of allowing the two bands' composition to be influenced by background values in open areas and to readily reach saturation in dense vegetation (Zhou *et al*., 2022). The NDVI ranged from -0.1110 to 0.7012 in the study area. A negative value like -0.1110 usually points out water bodies or built-up areas. The highest value, 0.7012, indicates dense and healthy vegetation. The result of NDVI analysis is shown in Figure 2.

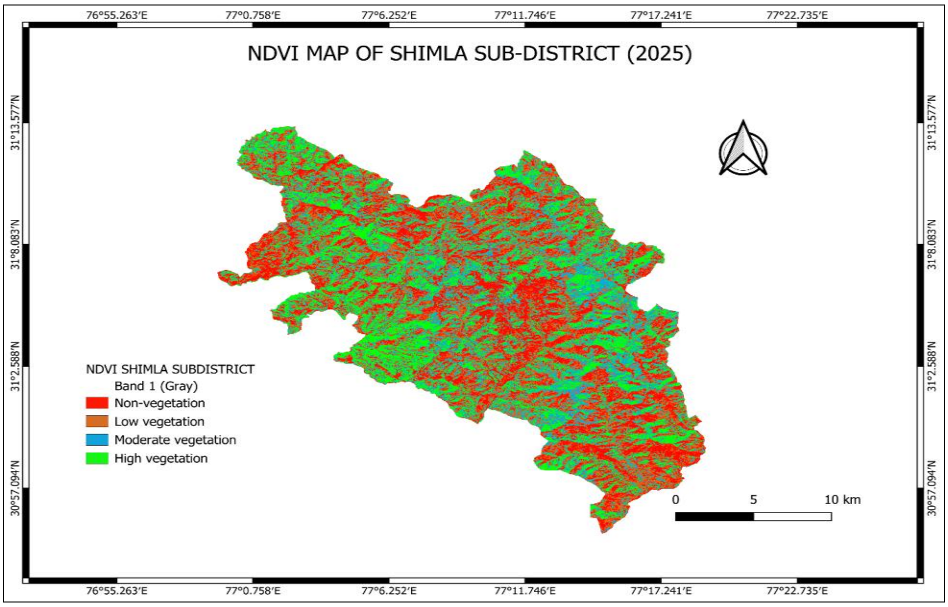

Fig 2: Spatial distribution of NDVI value in study area

The NDVI map revealed a distinct dichotomy most of the region belonged to Class 1 and Class 4 as shown in Figure 1. This indicates that the study area has both densely vegetated areas (possibly forested or reserved areas) and areas with very sparse vegetation (like urban buildings or exposed land). This difference in NDVI values helps identify areas where greenery can be increased or where urban development can happen. It also shows which places would benefit most from more vegetation. (Macarof & Statescu, 2017) [6].

3.2 Results of buildup index

The study area's built-up intensity was evaluated with the aid of NDBI analysis. The values of this index which varied from -0.4243 to maximum 0.4554 showed a combination of low-density development and natural surfaces. This study analyzed NDBI values and helped in reclassification of study area into four-classes as shown in Table 2.

Table 2: Classification of buildup depending upon NDBI range

Class	NDBI range	Land cover description
Class 1: Water/ Vegetation	< 0.0	Water bodies, forests, agricultural fields
Class 2: Bare land/Low Built-up	0.0 - 0.1	Open land, sparse or scattered structures
Class 3: Moderate Built-up	0.1 - 0.3	Residential zones, mixed development areas
Class 4: High Built-up	> 0.3	Dense urban cores, commercial/industrial areas

The results of this index area also showing dominance of natural land cover and sparse settlements as shown in Figure 3. Similar results were reported by (Zha *et al*., 2003) [14], who introduced NDBI to effectively distinguish built-up areas from other land covers using satellite imagery. Several recent studies, like (Xu, 2007) [13] and (Weng, 2012) [12] have confirmed that NDBI performs well in identifying urban footprints, especially when combined with NDVI for improved accuracy.

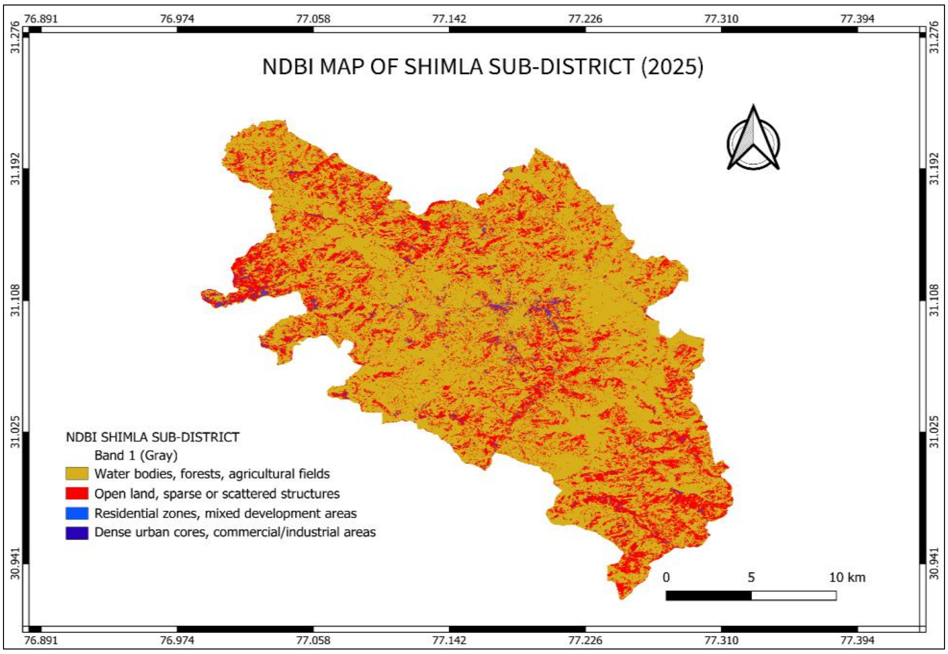

Fig 3: Spatial distribution of NDBI value in study area

Overall, the study area's vegetation cover and built-up intensity can be clearly understood from the NDVI and NDBI results. A comparatively unaltered landscape is highlighted by the predominance of natural land and minimal development. Future planning, land management, and environmental monitoring initiatives can benefit from these findings.

3.3 Correlation between NDVI and NDBI

To investigate the interaction between urbanization and vegetation cover in study area, a statistical correlation analysis was carried out between the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI). Pixel-wise values (approximately 170,000 records) were processed using Python in the Anaconda environment. Core libraries such as pandas were used for data management, scipy.stats for statistical analysis, and seaborn and matplotlib for data visualization. The Pearson correlation coefficient was calculated to assess the strength and direction of the linear relationship between NDVI and NDBI. The result revealed a negative correlation of r = -0.33 was obtained, indicating a moderate inverse relationship i.e. areas with higher built-up density tend to have lower vegetation cover, although the relationship is not very strong. The p-value of 0.0000 (or more precisely, $p<0.001$) further supports the statistical significance of this correlation, suggesting that the observed relationship is highly unlikely to have occurred by random chance. A scatter plot with a fitted regression line was created to visually depict this trend. The observed negative correlation, though moderate, still suggests that urban expansion has a noticeable impact on vegetation loss and highlights the importance of integrating ecological indicators into urban planning strategies**.** Scatter Plot of NDBI vs NDVI for assessing the relationship between urbanization and vegetation cover in study area is shown below in Figure 4.

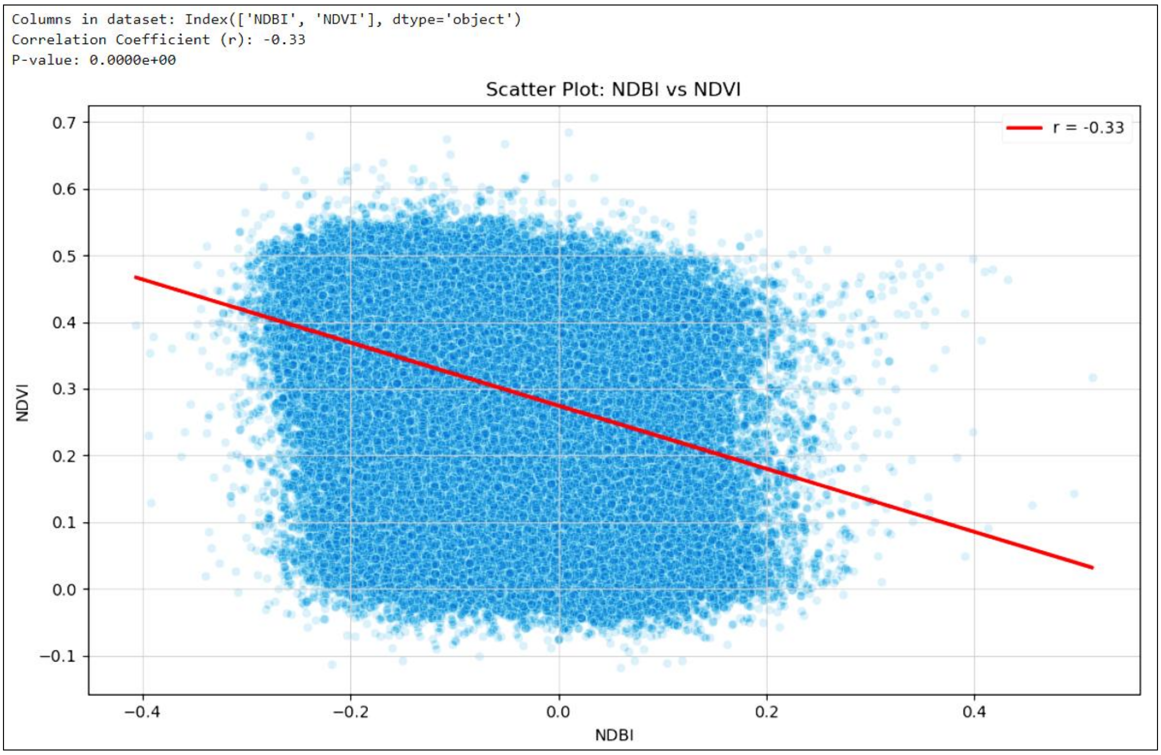

Fig 4: Scatter plot of NDBI and NDVI in study area for correlation analysis

Index	Min Value	Max Value	Bands Used (B)	Resolution	Correlation Cofficient (r)
NDVI	-0.1110	0.7012	4 & 8	10 m	
NDBI	-0.4243	0.4554	8 & 11	10 m	**-0.33**

3.4 Results of vegetation-built-up environment index

The spatial relationship between vegetation and built-up surfaces throughout the study area was examined using the Vegetation-Built-up Environment Index (VBEI). VBEI is an aggregated index based on NDVI and NDBI, employed in recent researches to characterize vegetation-urban development balance. It is not a regular index but has been successfully utilized in different urban stress analyses and can be applied to the study of vegetation-built-up dynamics in the study area. The Vegetation-Built-up Environment Index (VBEI) provided a clear spatial understanding of the balance between vegetation and urban surfaces in study area. VBEI values, derived from NDVI and NDBI, ranged from -1 to +1, with negative values indicating vegetation dominance and positive values representing built-up dominance. High VBEI values were concentrated in the city center and newly developing areas, highlighting zones of intense urban stress. In contrast, negative VBEI values were found along the forested and less disturbed outskirts, reflecting healthier vegetation cover as shown in Figure 5 below:

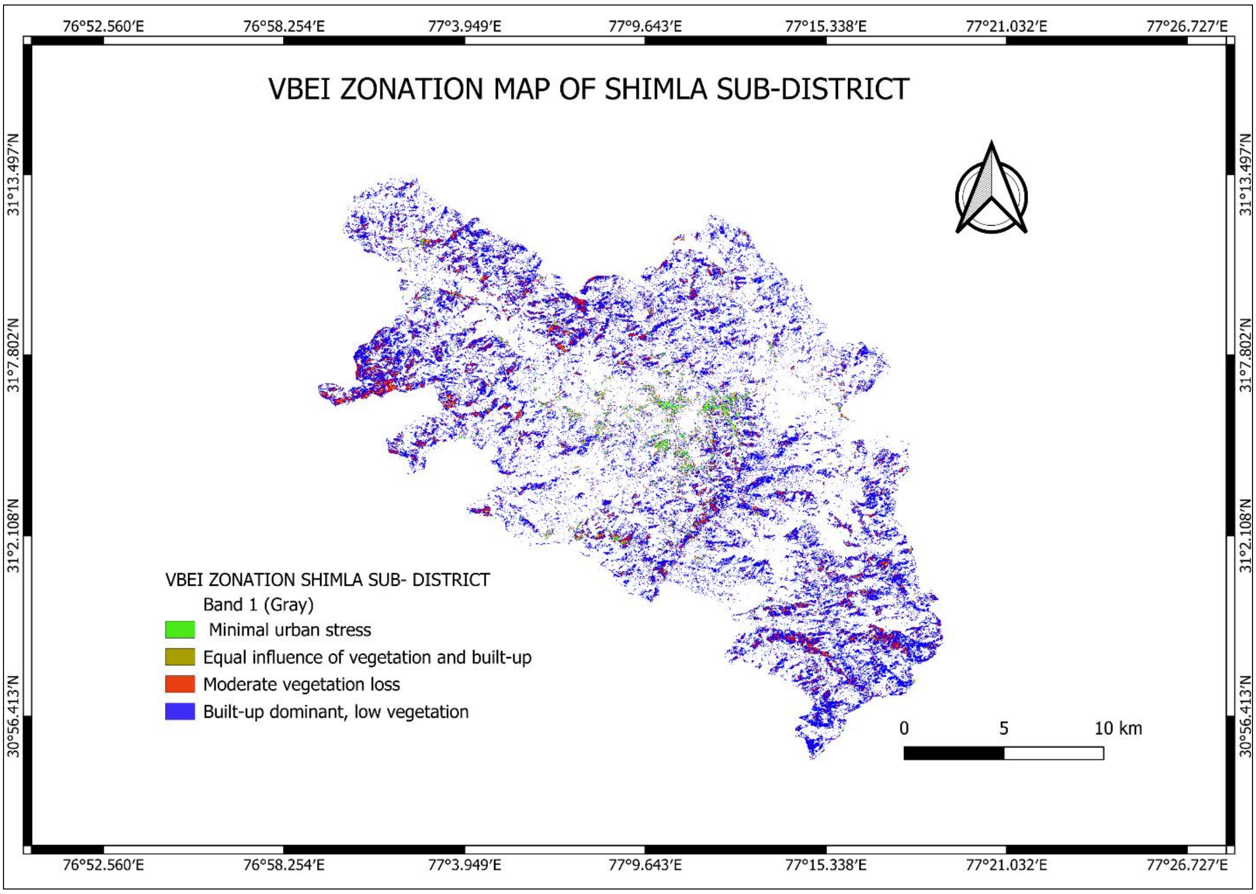

Fig 5: Spatial distribution of VBEI value in study area

To interpret these results meaningfully on the basis of VBEI values, the area under study was reclassified depending upon stress zones into four categories as given in Table 3:

Table 3: Classification of stress zones depending upon VBEI range

Zone	VBEI Range	Interpretation
High-Stress	0.5 to 1.0	Built-up dominant
Moderate-Stress	0.1 to 0.5	Moderate vegetation loss
Balanced	-0.1 to 0.1	Equal influence of vegetation and built-up
Vegetation-Dominated	-1.0 to -0.1	Dense vegetation, minimal urban stress

In raster processing, there were pixels that gave null or undefined values as a result of division by zero (when NDVI + NDBI = 0) were masked to avoid distortion in the analysis. The final zonation map according to VBEI classification distinctly revealed high-stress areas under urban pressure and low-stress areas with healthy vegetation. This assisted in confirming the results from NDVI and NDBI analysis and enhanced the understanding of vegetation loss patterns due to rapid urbanization in the area.

4. Conclusions

The current study evaluated vegetation health, intensity of built-up, and patterns of ecological stress in the study area using Sentinel-2 imagery and remote sensing indices, namely NDVI, NDBI, and VBEI. By synergizing geospatial analysis and correlation statistics, this study examined the ways in which uncontrolled urban growth is restructuring the natural terrain of this environmentally sensitive hill city. The NDVI image evidently demonstrated a patchy vegetation pattern. Highly vegetated regions were generally confined to forest cover and slope areas, while the urban centers and developing construction belts had very low NDVI values. On the other hand, NDBI revealed developing built-up hotspots in the central part of city as well as outer developing areas. Combined, these indices revealed an increasing disparity between natural green cover and hard urban infrastructure.

A negative correlation (-0.33) between NDBI and NDVI, with a significant p-value of 0.000, provides strong evidences of the adverse effects of urbanization on vegetation cover in Shimla. A negative correlation between NDVI and NDBI reaffirmed the reversal relationship i.e. more urbanization results in loss of vegetation and hence poses a great challenge for sustainable development. This correlation was not more than just a figure; it supported the spatial patterns that this study mapped, which further assisted in validating the accuracy of our interpretation. These results create a good case for integrated planning, taking into account both ecological sustainability and land use pressure. VBEI, an aggregate index formed by combining NDVI and NDBI, provided some additional information which enable us to categorize the study area into different stress zones. Urban zones of high ecological stress were marked by high values of VBEI which were identified within the center of study area and spreading outskirts. Conversely, forested and vegetation spots registered negative VBEI values, which represent a healthier state of the environment. Further managing null values in VBEI computation arising from zero denominators guaranteed that the data was reliable and hence prevented misleading results.

Overall, this study provides a straightforward but effective geospatial approach to assess ecological stress in rapidly urbanizing study area. The application of zonation and statistical verification enabled us to identify those places that require urgent intervention be it through vegetation reclamation, green infrastructure, or more stringent urban controls. The methodology adopted here is extensible, replicable, and translatable to other comparable landscapes. As Shimla develops, the problem is not merely to control development but to maintain the natural systems that sustain it. This study demonstrates how spatial information, remote sensing technology, and intelligent analysis may inform decision makers about the balance of urban expansion and environmental resilience.

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