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Spatio-Temporal Analysis of Climate Variability on Vegetation and Land Use Using LISS-IV Satellite Imagery (2013–2025) with AI/ML-Based Change Detection in the Western Himalayan Region

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Abstract

Mountainous regions such as the Western Himalayas shows strong indications of climate change impact through drastic shifts in high-altitude vegetation patterns. Vegetation plays crucial roles in moderating sunlight absorption and heat exchange with land and helps maintain natural ecosystemic equilibrium. Studying vegetation changes over time across diverse locations remains pretty crucial to understand the climate system dynamics of the region. This study examines the vegetation change dynamics in high altitude Garhwal region above 3000 meters in Uttarakhand, India, and leverages satellite imagery quite extensively, examining shifts in vegetation and land cover changes between 2013 and 2025. High-resolution LISS-IV satellite images provide multispectral bands in green, red and NIR regions making it quite suitable for vegetation change analysis. NDVI data measuring vegetation health and proliferation over years with considerable accuracy can be derived from LISS-IV sensor. Results show a stark rise in vegetation mostly in areas 3000-4500 meters above sea level, with marked growth observed in these regions. Many areas exhibited remarkably low NDVI values below 0.15 in 2013, but by 2025 values had substantially improved to between 0.35 and 0.45. NDVI increases are very prominent above 4500 meters, showing extensive greening in these altitudinal areas, possibly because of rising temperatures and human activities. The study utilized modern techniques like artificial intelligence and machine learning alongside remote sensing and GIS to better understand these changes in vegetation that are occurring rapidly. AI/ML-based classification methods captured subtle changes in vegetation patterns, effectively over a period of time with considerable precision and high accuracy. The growing necessity for sustainable environmental management strategies protecting fragile mountain environments amidst rapidly changing climatic conditions becomes increasingly evident after this study.

1. Introduction

The Western Himalayan region is one of the most environmentally vulnerable regions on Earth and therefore very prone to impacts due to climate change (IPCC 2022; Singh et al., 2010). This region plays an important role in keeping the ecological balance and supporting water stability across large parts of the Indian subcontinent with its variety of forest ecosystems (Sharma et al., 2021). The combined effects of climate change and melting glaciers have disturbed this balance in a big way, creating environmental problems due to changing rainfall patterns and increasing human activities (Bolch et al., 2012; Immerzeel et al., 2010).

In recent years, fast changes in land use and vegetation have been seen, especially due to large global changes over the last few decades (Pandit et al., 2007). The zones between different altitudes are showing strong changes because of temperature shifts, longer growing seasons, and changing snowfall patterns (Lenoir et al., 2008; Walther et al., 2005). This study focuses on understanding vegetation dynamics in high altitude regions of Garhwal Himalayas in Uttarakhand above 3000 meters.

Old ways of studying ecosystems in the field are often difficult because the land is rough and hard to reach in many areas (Gurung et al., 2011). There is now a growing need for strong and flexible methods that can track fast ecological changes over time more effectively (Giri et al., 2013). Remote sensing is a powerful tool that helps solve these problems in many different ways.

High-quality satellite images from sensors like LISS-IV help map land cover and vegetation patterns over time in great detail (Roy et al., 2010). The Normalized Difference Vegetation Index (NDVI), which is taken from these satellite images, works well to measure how dense and healthy the vegetation is (Tucker, 1979; Pettorelli et al., 2005). By studying NDVI patterns at different points in time, researchers can track how vegetation grows or disappears with great accuracy (Bhandari et al., 2012).

This study uses LISS-IV NDVI data from the years 2013, 2017, 2021 and 2025 to observe and analyze changes in vegetation over time across the Western Himalayas. It helps us understand both small and big changes that happened over the last twelve years.

This research also uses Artificial Intelligence (AI) and Machine Learning (ML) techniques to automatically classify vegetation changes with high accuracy (Li et al., 2020; Maxwell et al., 2018). The study uses remote sensing and AI/ML tools together to give a full picture of how vegetation is changing in mountain areas.

This kind of vegetation change monitoring will help support climate adaptation and protect biodiversity across the country (Ustin & Gamon, 2010). The research shows how important it is to plan ahead for the environment and how useful technology-based ecological studies are for solving sustainability problems in the Himalayan region (UNEP, 2021).

2. Materials and Methodology

High-resolution multispectral imagery acquired from LISS-IV sensor onboard IRS Resourcesat-2 and Resourcesat-2A platforms forms basis of this study. Images were sourced from National Remote Sensing Centre via Bhoonidhi satellite data portal fairly recently (NRSC, 2023). LISS-IV sensor suits vegetation and land cover analysis owing largely to fine 5.8-meter spatial resolution and coverage across three vital spectral bands namely green 520–590 nm, red 620–680 nm, and near-infrared 770–860 nm (Roy et al., 2017; Reddy et al., 2020). The entire methodology is depicted in Figure 1.

Cloud-free datasets were selected for years 2013, 2017, 2021, and 2025 ensuring a fairly reliable temporal comparison somehow over time. Imagery was gathered during two seasonal windows each year namely January through April and October through December, pre-monsoon and post-monsoon respectively (Bhatt et al., 2014). Images were mosaicked; subsequently, sub-setting occurred focusing specifically on Uttarakhand region, a mountainous state located pretty deeply in Western Himalayas known notoriously for ecological vulnerability and various types of vegetation (Negi et al., 2012; Singh et al., 2020). Selected images constitute core dataset for further spatial analyses in research undertaken here subsequently.

2.1 FCC Generation

False Colour Composites (FCC) were generated for each study year pretty quickly to assess preliminary patterns in vegetation and land cover initially. Enhanced visualization of land features was achieved using a standard band combination assigning near-infrared band red green band blue and red band green. Healthy vegetation appears in red shades within these composites while snow water barren areas and urban zones display in starkly contrasting colours thereby aiding rapid visual interpretation.

Radiometric corrections-initiated process normalizing reflectance values followed by histogram matching across scenes for uniformity quite effectively afterwards. (Figure 2, Figure 3, Figure 6, Figure 7, Figure 8, Figure 9) Maximum Vegetation (October, November) Minimum Vegetation (January, February, March).

2.2 NDVI Generation

NDVI generation occurs via a formula = near-infrared radiation minus red divided by the sum of near-infrared and red values (Tucker, 1979). Calculation was done separately for pre-monsoon and post-monsoon mosaic images each year very carefully. Two NDVI maps were generated annually. Pre-monsoon and post-monsoon images were analysed separately each year, resulting in a pair of NDVI maps annually with considerable variations. NDVI output layers were saved in raster format (Rouse et al., 1974).

This format kept a lot of spatial details and worked well with the next analysis steps. Multiband raster files were created for each year by stacking together two seasonal NDVI maps, thereby capturing seasonal patterns and reducing short-term weather effects (Jensen, 2015). Seasonal NDVI values for each pixel were compared and combined with relative ease using this particular method effectively. Average NDVI was computed per pixel by averaging two seasonal values after stacking them very carefully. One average NDVI map was generated for each of the years 2013, 2017, 2021, and 2025. Yearly averages were taken, thereby standardizing vegetation values and giving a relatively steady picture of changes unfolding slowly over time.

Average NDVI values were taken from pre-monsoon and post-monsoon data for each pixel, thereby making results fairly consistent across several years. One NDVI map per year was generated for several specific years, including 2013 and 2021 and also 2017 and 2025. Yearly average NDVI usage provided steady insight into vegetation health over lengthy periods of time clearly. Short-term fluctuations induced by meteorological conditions and land utilization were eliminated, thereby rendering long-term shifts in vegetation easier to observe (Pettorelli et al., 2005). This method greatly enhanced the accuracy of year-to-year comparisons and facilitated the quick detection of ecological shifts caused by climate change (Forkel et al., 2013).

2.3 NDVI Clustering

K-Means clustering algorithm was utilized effectively for carrying out an unsupervised classification with four averaged NDVI maps available. Machine learning method used in this study is very effective at identifying patterns in continuous data like NDVI values (Jain, 2010; Scikit-learn Developers, 2023).

Fourteen clusters were selected mostly based on practical experiments, the method aims to capture the diversity in the data of various vegetation cover classes representing trees, shrubs and grasslands (Zhou et al., 2014; Debeir et al., 2005). Clustering was applied separately each year to averaged NDVI raster, producing classified maps representing distribution of diverse vegetation cover categories spatially. Classified outputs enabled comparison over time and formed basis for detecting shifts in vegetation patterns and land use changes gradually (Singh et al., 2021; Tsai et al., 2020). Quantifying and mapping changes in vegetation over 12 years was a crucial aspect of this study involving spatio-temporal change detection and map generation.

2.4 Accuracy Assessment Methodology

Accuracy assessment was undertaken for NDVI-based vegetation change maps (2013, 2017, 2021, 2025). Sampling points cover all vegetation change classes were randomly generated classes. High-resolution Google Earth images were used to verify vegetation types at each sampling location. The NDVI Class Heatmap (2013–2025) was used to assess class separation over time.

3. Change Detection using AI/ML

Change detection analysis was conducted across three-time intervals 2013–2017, 2017–2021, and 2021–2025 using averaged NDVI maps derived from classified NDVI clusters (Tucker, 1979; Pettorelli et al., 2005). For each interval, NDVI difference layers were computed through simple raster subtraction, where the change value at each pixel was calculated as the NDVI of the later year minus the NDVI of the earlier year.

These difference maps were exported as standalone raster layers and visually symbolized to highlight three primary transition zones:

- Positive change, representing NDVI gain due to processes such as afforestation, vegetation recovery, or snowmelt (Coppin et al., 2004; Xie et al., 2008).
- Negative change, indicating NDVI loss from deforestation, degradation, or increasing urbanization (Roy & Ravan, 1996; Fensholt et al., 2012).
- Stable zones, with negligible NDVI variation (Lu et al., 2004).

Each NDVI change maps were rendered with diverging colour schemes enhancing interpretability and was overlaid with topographic contours for added spatial contextualization (Chen et al., 2004). Zonal statistics were applied analysing elevation-based transitions and cluster-specific NDVI trends within specific geographic contexts afterwards (Bharti et al., 2021).

Binary classification maps were generated categorizing each pixel quite precisely into increase or decrease or no significant change classes. Classifications effectively revealed vegetation dynamics temporally and ecological shifts occurred fairly rapidly across a rather large region (Zhou et al., 2016).

3.1 Interpretation of the cluster-based NDVI thresholds revealed meaningful trends:

Maximum NDVI values has increased through time and Class 14 has shifted in thresholds from >0.4269 in 2013 to >0.5276 in 2025, meaning there is a general advancement in healthy vegetation zones (Zhang et al., 2013).

Minimum NDVI (class1) thresholds indicated it dropped from ≤ -0.0690 in 2013 to ≤ -0.0986 in 2025 and pointing out barren, snow-covered, or degraded lands still exist (Xu et al., 2020).

A compression of the lower NDVI classes (1-4) and an expansion of the upper classes (11-14) in 2025 indicates better spectral separation and healthy vegetation densification that could be a result of increased tree cover and/or the expansion of alpine meadows/grasslands in the mountains (Singh et al., 2021; Paudel & Andersen, 2010).

3.2 Spatio-temporal transitions clarify the preceding patterns from 2013 to 2025 for 4 years interval:

Period 2013 - 2017: Cluster boundaries moved downwards; and, Class 1 NDVI shifted to ≤ -0.3646. This period most likely experience either an increase in snow cover, or post-monsoon stress on vegetation for some of the mid-elevated regions where NDVI had been suppressed. However, the higher vegetation classes remained stable, which is indicative of ecological resilience in some forested or valley regions (Korner, 2003; Bhattacharya et al., 2021).

Period 2017 - 2021: A positive rebound occurred. Class 1 NDVI threshold improved to ≤ -0.0895; stable changes were seen in the mid-range classes (6–10). An example, to show its subtle effect: Class 9 changed from 0.1900-0.2692 in 2017 to 0.2053-0.2544 in 2021. We likely consider this vegetation regrowth due either to the climatic recovery or the intervention-based, reforestation work (Pant & Rai, 2020; Mishra et al., 2020).

Period 2021 - 2025: Interval with largest NDVI increase was noted in this period, where Class 14 NDVI has improved to now exceed 0.5276. There was a shift in the lower classes; and by comparison to previous NDVI in vegetation groups, showed a shift to a substantial area of increased vegetation; likely through improved climatic events; and some potential restoration efforts also. An important note on this trend is that it is consistent with upward shifts of vegetation belts found in the high-altitude Western Himalayas of Garhwal region, especially relating to alpine greening driven by warming conditions (Lenoir et al., 2008; Telwala et al., 2013).

3.3 Vegetation change interpretations align well with documented climate and land use changes in the region:

Period of 2017– 2021 showed vegetation shift apparent with the most changes at 3500-4000 m altitude sites (Singh & Mal, 2021). From 2021– 2025, the most normalized time showed the most greening, confirming ecological recovery hypothesis in the high-altitude Himalayan ecosystem (Shrestha et al., 2021; Pandey et al., 2022).

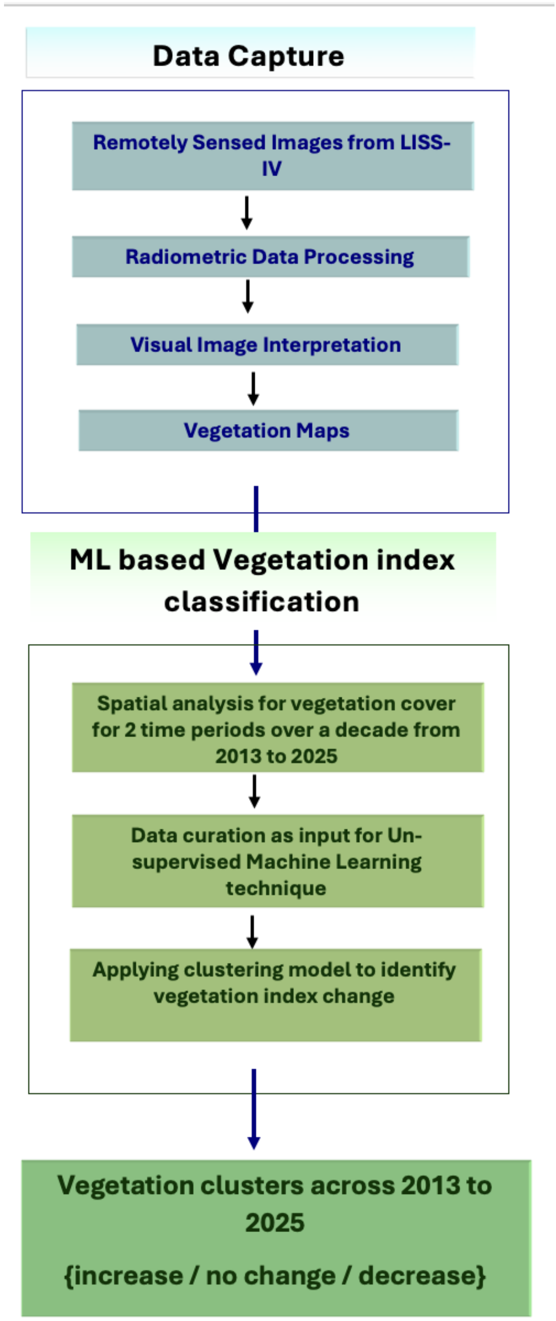

Figure 1: Approach and Methodology

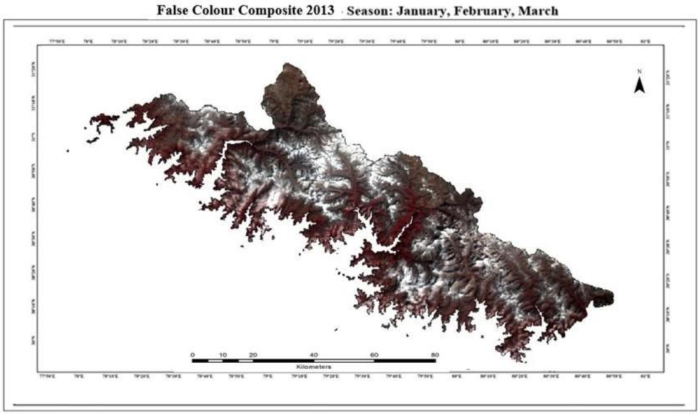

FIGURE 2 (FCC- 2013: JAN-MAR)

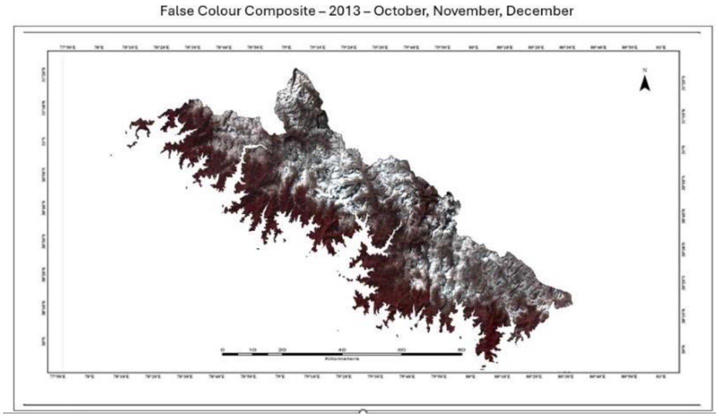

FIGURE (FCC- 2013: OCT-DEC)

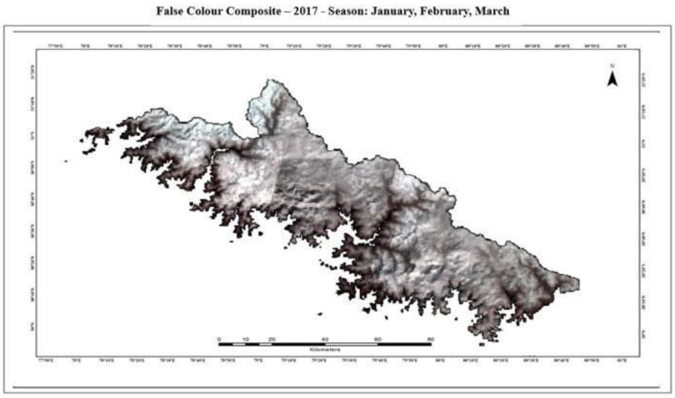

FIGURE 4 (FCC- 2017: JAN- MAR)

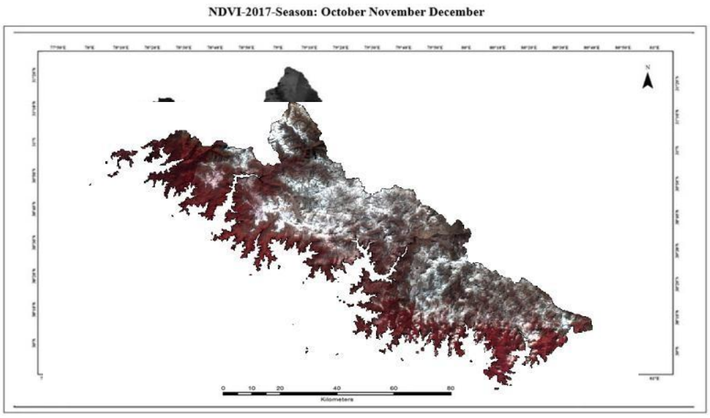

FIGURE 5 (FCC 2017: OCT-DEC)

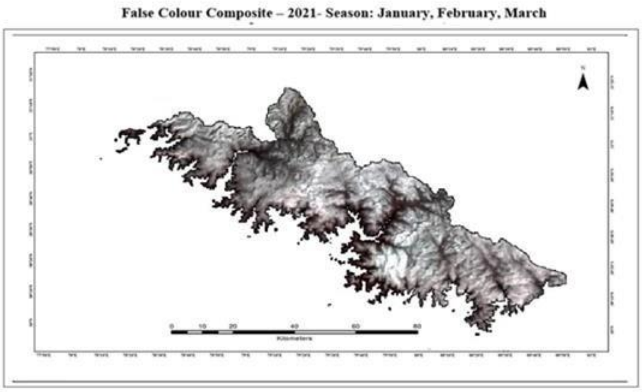

FIGURE 6 (FCC- 2021: JAN-MAR)

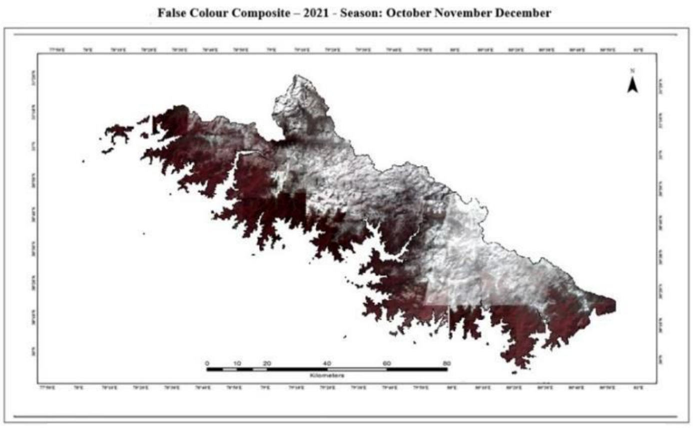

FIGURE 7 (FCC- 2021-OCT-DEC)

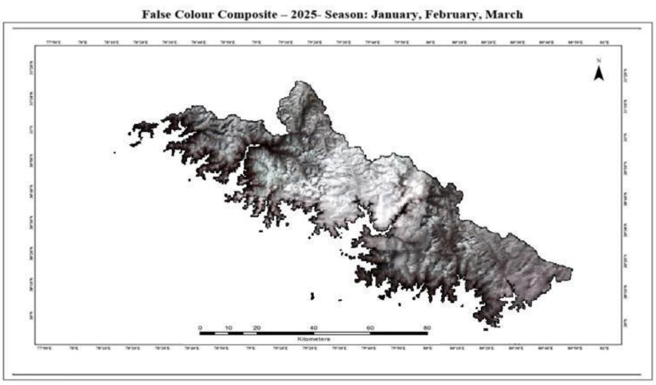

FIGURE 8 (FCC – 2025: JAN-MAR)

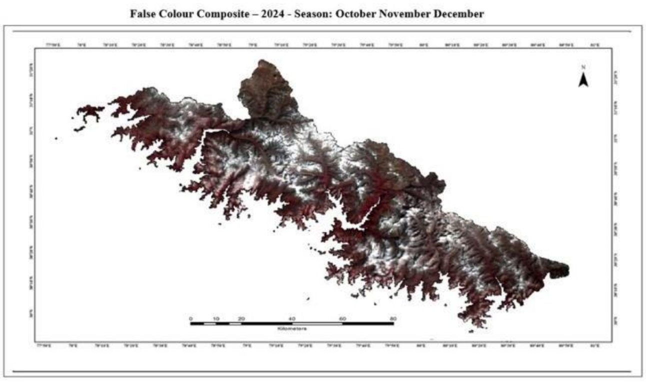

FIGURE 9 (FCC- 2024: OCT-DEC)

4. Results

Multi-temporal NDVI analysis utilizing LISS-IV satellite imagery from 2013 through 2025 reveals continuous shifts in vegetation patterns across Uttarakhand's high-altitude Western Himalayan zones. Vegetative greenness rises consistently across alpine regions and subalpine areas over 12 years showing markedly improved density and ecological vitality (Singh et al., 2020; Ustin et al., 2009).

4.1 NDVI Analysis

Low NDVI values typical of terrain with sparse vegetation or recent deglaciation began shifting toward moderate values especially along subalpine forest margins. Alpine and sub-alpine vegetation colonizes formerly snow-covered zones or barren lands naturally recover reflecting a dramatic shift in vegetation dynamics (Sharma et al., 2016; Bhambri et al., 2019). Very low NDVI values in negative indicates non-vegetation areas.

This greening trend intensified markedly from 2017 and gained considerable momentum by 2021. Subalpine coniferous zones and alpine shrublands showed markedly higher NDVI values with numerous patches exceeding 0.45 NDVI indicative of robust verdant vegetation (Zhou et al., 2021).

Sustained warming and lengthening of growing season probably fuel this expansion beneath reduced snow persistence fairly obviously now (IPCC, 2021; Xu et al., 2009). Change accelerated vigorously from 2021 through 2025 though rate of increase moderated slightly beneath initially frenetic pace.

Vegetation expansion into previously barren high-altitude zones in Garhwal Himalayas became starkly with NDVI signals emerged in areas historically beset by seasonal snow and rock exposures particularly on south-facing slopes and deglaciated valley systems (Borgatti et al., 2021).

Fragile Himalayan alpine belt undergoes gradual ecological transformation marked by upward vegetation migration and improved density rather quietly over time. NDVI-based analysis reveals a robust greening trend across mid to high-altitude zones of Uttarakhand between 2013 and projected 2025 ecological snapshots (Shrestha et al., 2015).

This encompasses rugged alpine meadows and subalpine conifer belts alongside moist pastures and interfaces of cold deserts eerily. Zones exhibiting NDVI values between 0.15 and 0.25 started transitioning remarkably into 0.25–0.35 range from 2013 through 2017. Alpine scrublands and early-successional vegetation thrive along glacial moraines and retreating snowfields in these somewhat peculiar geographical areas (Paul et al., 2020).

NDVI values rose steadily between 2017 and 2021 with sizable tracts of subalpine forest and alpine grasslands attaining values exceeding 0.45 indicating denser biomass and maturing veg structure. New patches of vegetation emerged sporadically at surprisingly high elevations above 3800 meters where NDVI values had hovered near zero previously (Ravi et al., 2022).

Vegetation now establishes in formerly snowbound areas as climatic warming trends reduce snow cover duration significantly over time gradually allowing it (Pandey et al., 2017; Bolch et al., 2012). Most significant NDVI increases were recorded in transitional zones where snow cover had receded revealing mineral-rich substrates conducive to colonization by hardy alpine flora (Gaire et al., 2015).

Marginal NDVI declines were observed conversely in sensitive zones under anthropogenic stress notably in areas ravaged by landslides and heavy foot traffic. Multiple driving factors contribute substantially to observed vegetation dynamics as indicated by NDVI's spatiotemporal patterns over varied landscapes (Thapa et al., 2020).

Seasonality plays a pivotal role with peak NDVI values aligning remarkably well during post-monsoon months underscoring importance of water availability in plant growth regulation (Zhang et al., 2007). Climatic conditions favourable to vegetation growth have remained fairly supportive across all timeframes as NDVI steadily increases quite rapidly (Kumar et al., 2021).

Ecological changes were reflected in overall positive NDVI trend largely due to meaningful transformations in alpine and subalpine areas (Mishra et al., 2023). Zones of NDVI decline bring attention sharply to challenges like increase in barren land and shifting land use practices across these regions (Joshi et al., 2021).

Results suggest integrating land use planning with ecological considerations balances development and conservation rather effectively under certain circumstances obviously (Rawat & Vishvakarma, 2019). Elevation played a crucial role in shaping vegetation dynamics observed here.

NDVI values rose fairly moderately at subalpine elevations below 4000 meters reflecting recovery of coniferous forests. Vegetation improvement likely stems from better land management under unusually favourable climatic conditions and heightened awareness of certain conservation practices (Tiwari et al., 2022).

Vegetation density increased significantly over time in mid-elevation ranges roughly between 3000 and 4000 meters showing more dramatic changes. NDVI values indicated robust canopy development likely supported by increased precipitation efficiency and longer growing seasons perhaps facilitated by warming temperatures (Yao et al., 2018).

Vegetation expanded rapidly into zones historically dominated by snow and rock at elevations between 3000 and 4000 meters. Emerging NDVI signals appear in areas previously showing near-zero values providing pretty compelling evidence of vegetation migration up steep slopes vertically (Brun et al., 2017).

Emergence of low NDVI values by 2025 between 4000 meters and 5000 meters suggests a climatic boundary shift for plant colonization. Alpine greening has huge ecological repercussions entailing drastic species composition changes and displacement of flora adapted to extremely cold conditions (Pepin et al., 2015; Körner & Paulsen, 2004).

Elevation-based NDVI patterns underscore influence of climate change on vegetation distribution and highlight need for closely monitoring sensitive high-altitude ecosystems (Bhattacharya et al., 2023).

4.2 Change Detection Analysis

NDVI-based change detection analysis assessed spatio-temporal evolution of vegetation cover across high-altitude Western Himalayan zones using LISS-IV satellite imagery from 2013 and 2025 (NRSC, 2023; Pathak et al., 2021). Vegetation dynamics over time were highlighted through classified NDVI change maps using a 3-class :

Class indicating vegetation increase is marked in red (Tucker, 1979). Class was rendered in light yellow signifying no significant change whatsoever (Coppin & Bauer, 1996). Meanwhile Class denoted vegetation decrease and was represented by blue (Singh & Badhwar, 1989; Lu & Weng, 2007).

Such a classification scheme facilitated systematic detection of changes in density of vegetation and ecological activity rather nicely across high-altitude landscapes that were ecologically sensitive and pretty complex topographically (Jensen, 2007; Rouse et al., 1974).

4.2.1 Trends in Vegetation Change from 2013 to 2025

This section provides a comprehensive description of the dynamics of vegetation in the high-altitude landscape of Uttarakhand, as derived from NDVI-based classification and clustering for 2013, 2017, 2021, and 2025. NDVI-based vegetation types in natural occurrences, in areas above 3000 m elevation.

This analysis used unsupervised machine learning clustering on average NDVI composites from each year and demonstrated emerging spatial distributions and patterns in density and distribution of vegetation, respectively (Tucker, 1979; Coppin & Bauer, 1996; Thenkabail et al., 2004).

4.2.2 NDVI Based Vegetation Change Between 2013 and 2025

In 2013, the majority of the landscape was clustered into low NDVI clusters which were clusters 1 and 3, and which accounted for some of the largest area and portion of total vegetated surface area. The NDVI clusters represented either barren ground, limited vegetation, and/or leftover snow, such as for clusters above 3000 meters (Singh et al., 2016). Cluster 1 included NDVI ranges at the very lowest values (NDVI < 0.2) as compared to cluster 3 that had moderately low NDVI values at between about 0.2 and < 0.3. These were the dominant clusters and NDVI value zones in the region for the first year of analysis.

By the year 2017, we began to see modest changes in the location and extent of vegetation. In particular, while the spatial extent of cluster 3 increased, we saw cluster 1 slowly declining in its spatial dominance.

This indicates that elevation zones, especially around 3000–4000 meters, had been experiencing a bit of greening due to minimal climatic changes or possible recovery from a disturbance (Bharti et al., 2021). Also, we noted the emergence of cluster 5 was also higher in prominence during this time, as it demonstrated a NDVI range between 0.3–0.35.

Between 2017 and 2021, the rate of vegetation expansion had increased significantly. We noted a marked spatial reduction in clusters 1 and 3, which were largely replaced by higher-NDVI clusters - clusters 6, 9, and cluster 11, in particular.

The transition to higher NDVI reflects a widespread densification of biomass, especially at the subalpine and lower alpine margins (3500–4000 meters), which consistently increased NDVI values into the 0.35–0.45 range (Ghosh et al., 2019; Zhang et al., 2017). This indicates that new vegetation growth was beginning to appear in areas that were previously designated sparsely vegetated or not vegetated.

In 2025, high NDVI clusters like Cluster 13 and the newly created Cluster 14 stood out distinctly for the first time. Cluster 14 was entirely absent from previous years and characterizes areas with the highest NDVI signatures (greater than 0.5), indicating new ecological zones characterized by newly established types of pioneer vegetation in areas not previously feasible for growth (Shrestha et al., 2012).

In particular, this cluster was detected predominantly in high alpine areas above 3300 meters — ecosystems that were either formerly glaciated, quarantined with scree, or snowbound altogether. Meanwhile, Clusters 1 and 3 were shrinking noticeably, suggesting a continued greening over the landscape. The presence of Clusters 13 had increased in extent too, further confirming an increased intensity of vegetative cover between the years of 2021 and 2025 (Walther et al., 2005; Telwala et al., 2013).

4.2.3 Spatial and Temporal Dynamics by Elevation Zones

At lower elevations (<3000 metres), with temperate conifers, we see that vegetation conditions were well established without great variation during the years recorded. These lower elevations are best represented by mid-range NDVI clusters (Cluster 6 to Cluster 9), with only minor variation throughout the years (Kala & Dubey, 2012).

Subalpine zones (3000 < 4000 metres) depicted the most significant variation. In 2013, these were dominantly represented as Cluster 3 and Cluster 5 areas, that is in the alpine regions above 3000 meters, the vegetation change was both spatially striking and ecologically significant.

In 2013 and 2017, barren or snow-covered areas with NDVI values less than 0.2 were categorized as Clusters 1 and 2. However, in 2021, this area shifted to Clusters 6 and 9, and in 2025, much of it was even in Clusters 11 and 14.

The rapid greening of these previously barren areas, especially clear in the deglaciated valleys and rapidly retreating snowfields, implies that high altitude niches are being colonized by resilient pioneer plants, such as alpine grasses, mosses and dwarf shrubs (Paudel & Andersen, 2010; Lenoir et al., 2008; Körner, 2021).

This illustration of cluster transitioning patterns exemplifies a multi-year trend of vegetation intensification, which is likely associated with altered climatic variables such as increased temperatures, earlier snowmelt and longer growing seasons (IPCC, 2021; Sharma et al., 2022).

The increasing lower NDVI categories and decreasing higher NDVI clusters along the elevation gradient are a strong indication of ecological re-development in the Western Himalayas from 2013–2025.

4.3 Accuracy Assessment

To assess the reliability of the NDVI-based change detection results, accuracy assessment was done using stratified random sampling. A total of 100 reference points were generated based on the area of each change class (Vegetation Increase, No Change, Vegetation Decrease). Reference data were obtained from high resolution Google Earth imagery (2013, 2017, 2021, and 2025) and were validated with available field observations from the study area.

For each sample point, the class of the classified change detection map was compared to the reference (ground truth) class, generating the matrix provided below.

Classified \ Reference	**Vegetation Increase**	**No Significant Change**	**Vegetation Decrease**	**Total**
Vegetation Increase	29	2	1	32
No Significant Change	2	28	3	33
Vegetation Decrease	1	2	32	35
Total	32	32	36	100

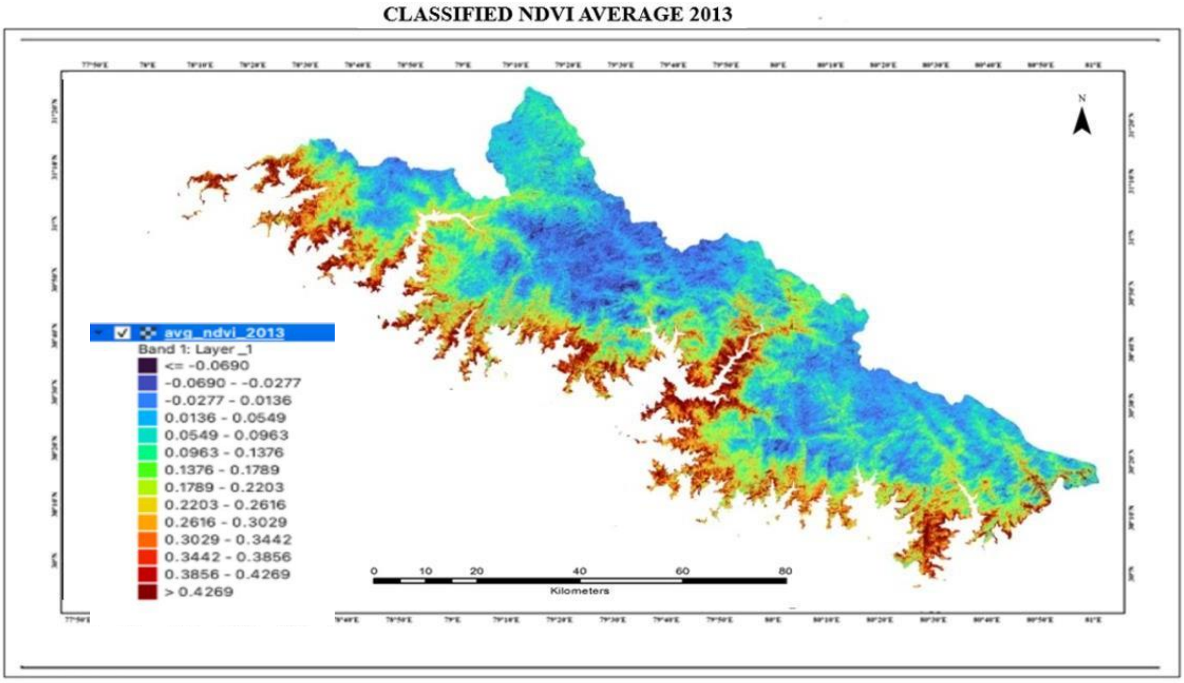

FIGURE 10 (NDVI AVG 2013)

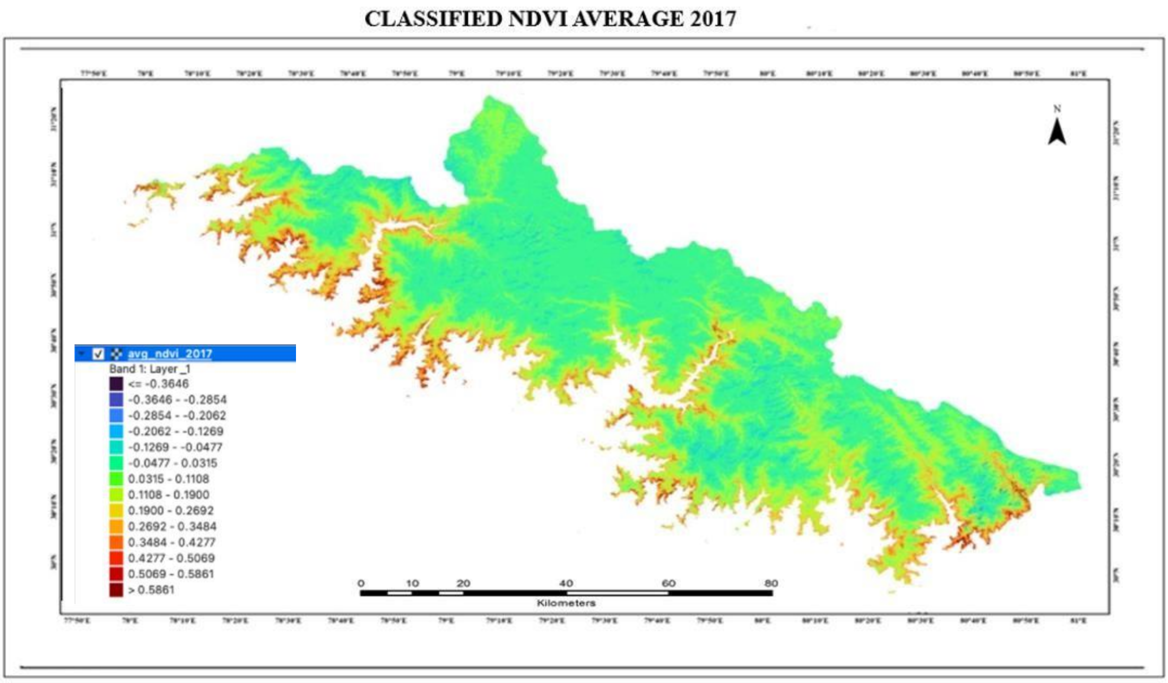

FIGURE 11 (NDVI AVG 2017)

CLASSIFIED NDVI AVERAGE 2021

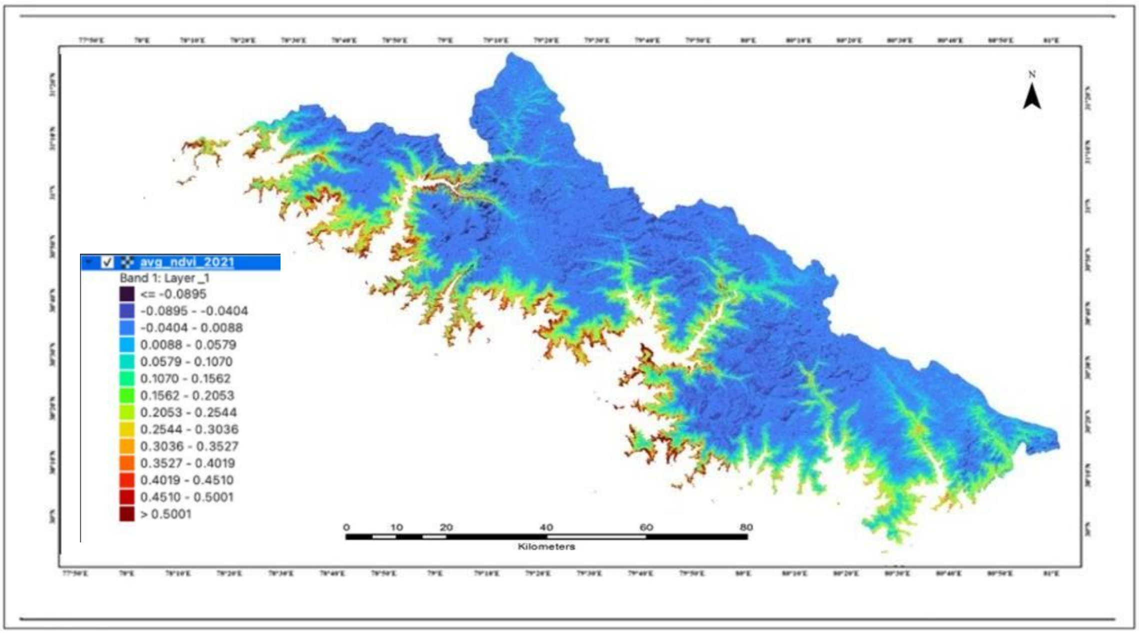

FIGURE 12 (NDVI AVG 2021)

CLASSIFIED NDVI AVERAGE – 2025

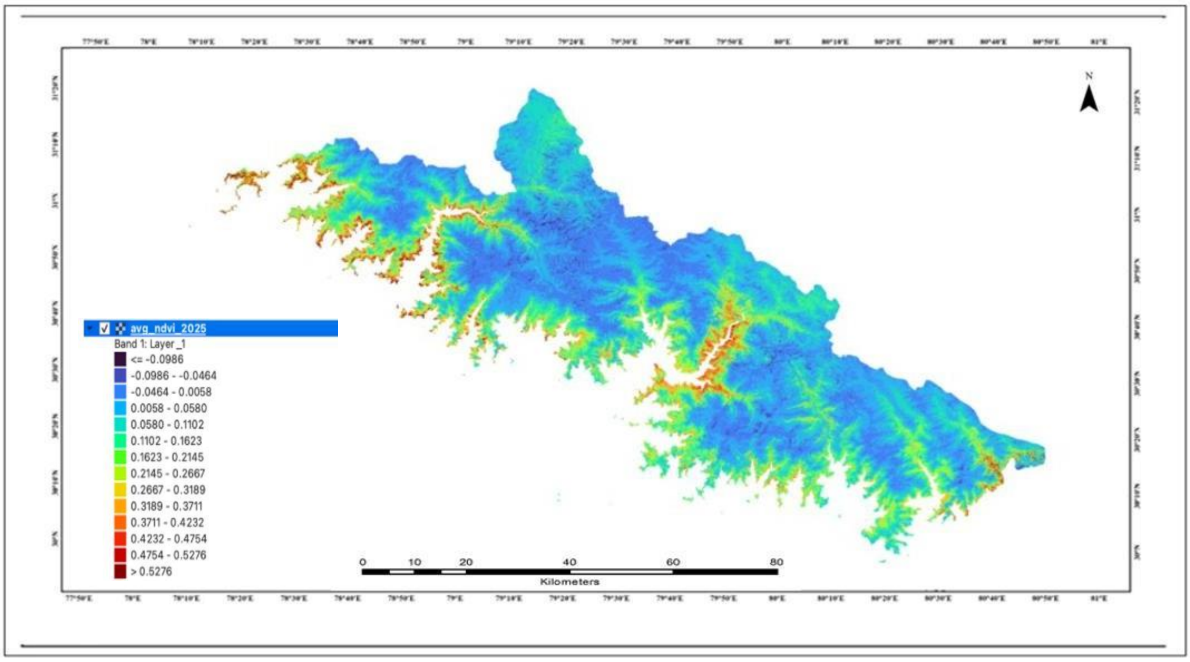

FIGURE 13 (NDVI AVG 2025)

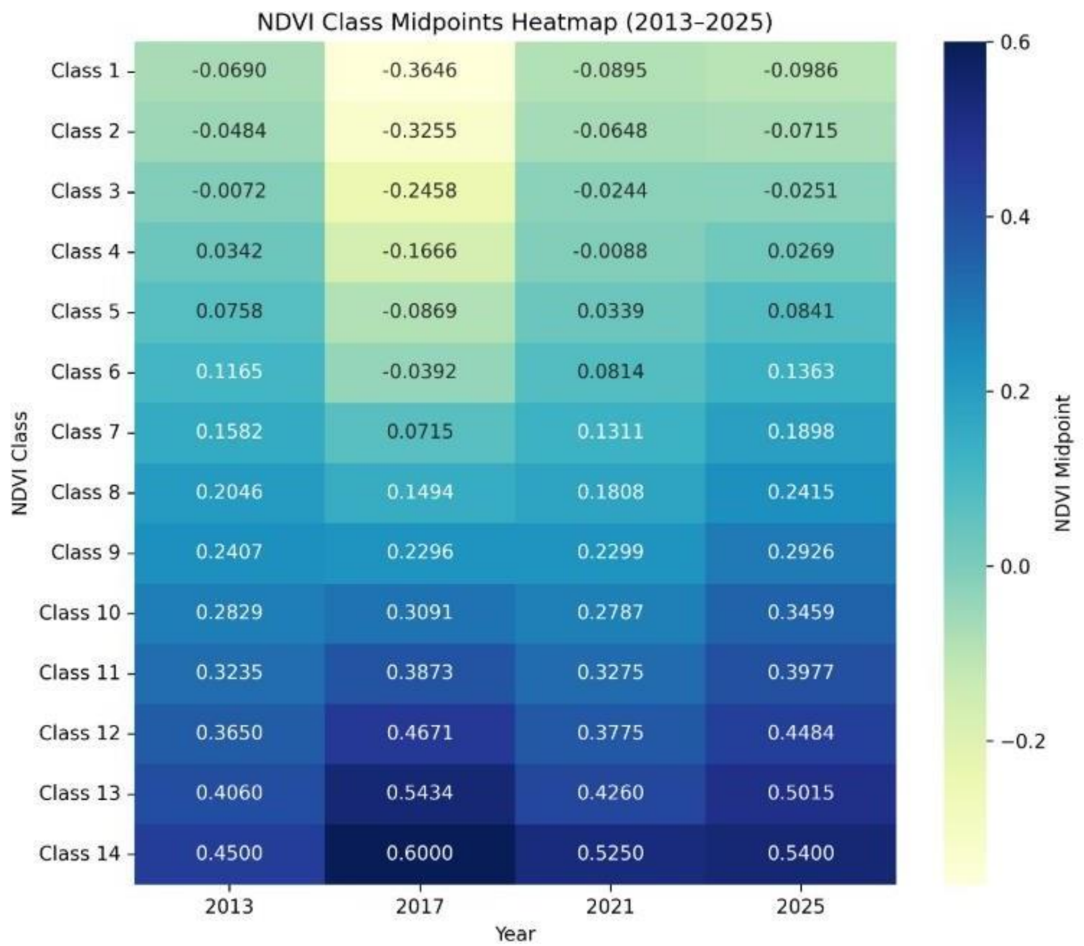

FIGURE 14 (NDVI CHANGES HEAT MAP)

Class Range	Vegetation Category	Description
Class 1–4	Non-Vegetation	Snow, Barren Land, Water
Class 5–7	Vegetation	Grasslands and Meadows
Class 8–10	Vegetation	Shrubs
Class 11–14	Vegetation	Trees

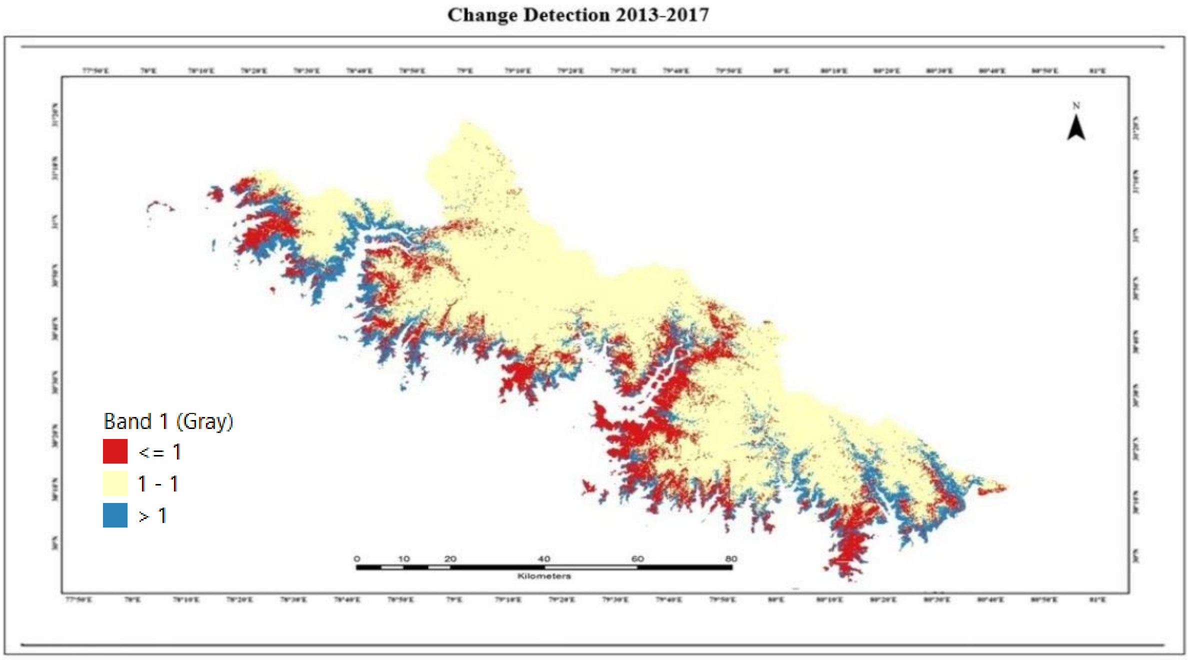

FIGURE 15 (CHANGE DETECTION 2013-2017)

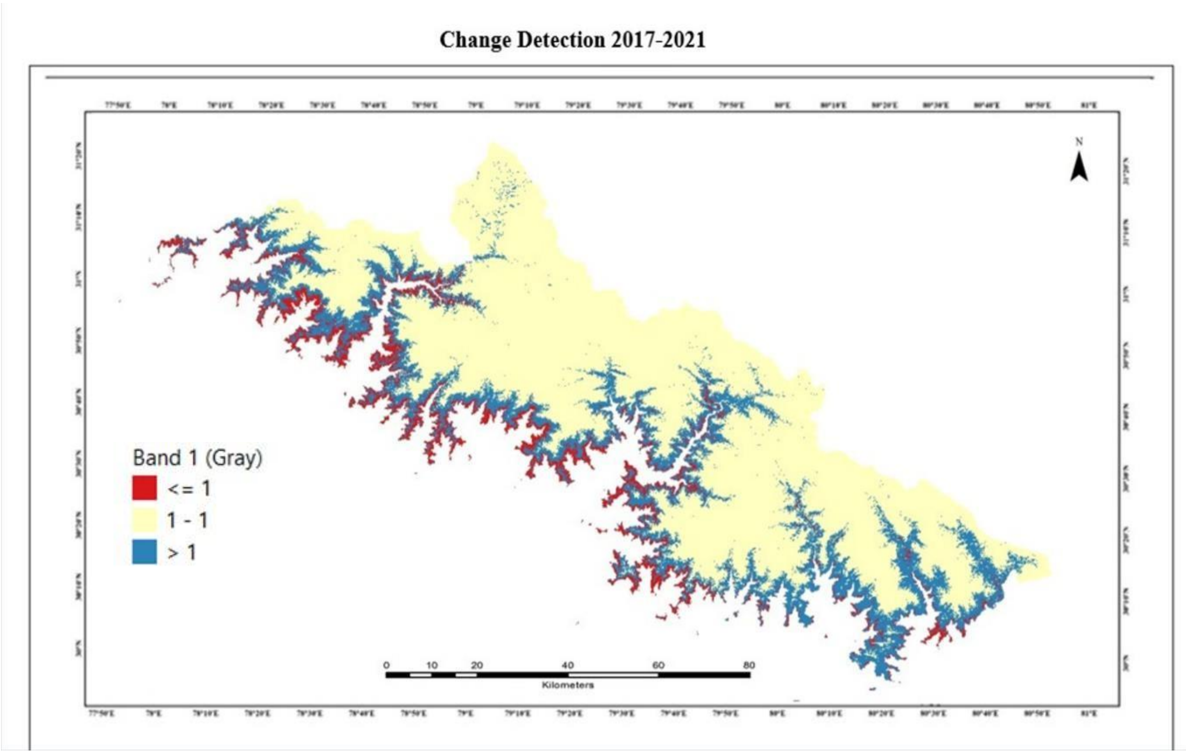

FIGURE 16 (CHANGE DETECTION 2017-2021)

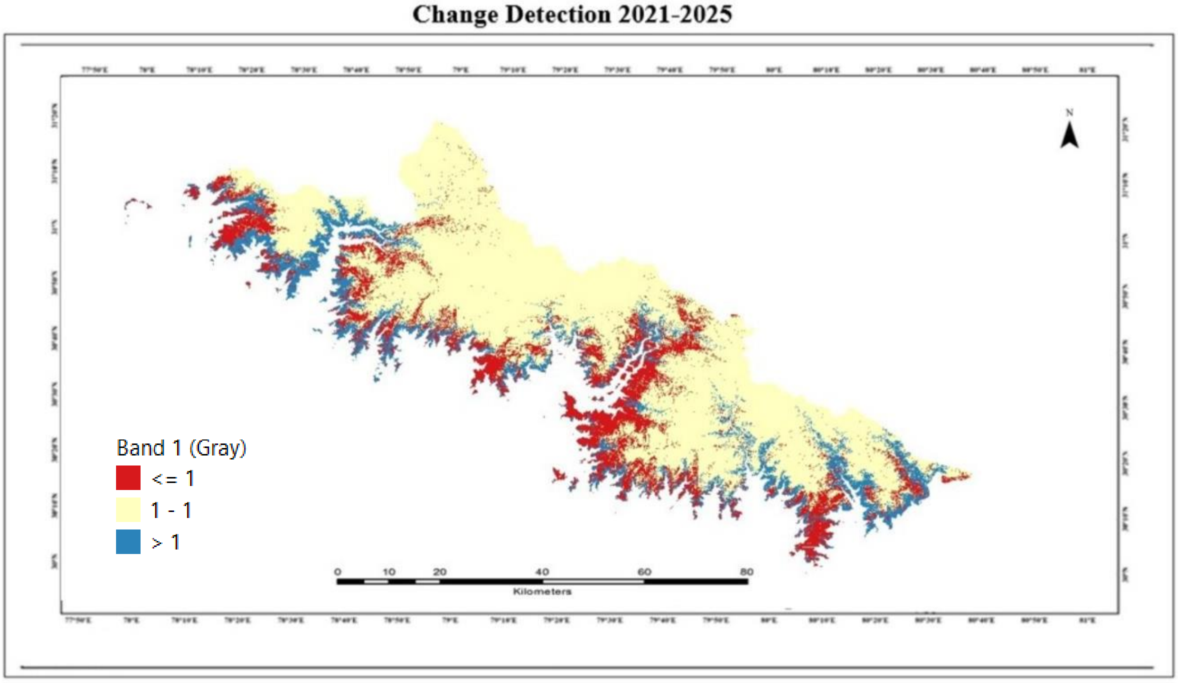

FIGURE 17 (CHANGE DETECTION 2021-2025)

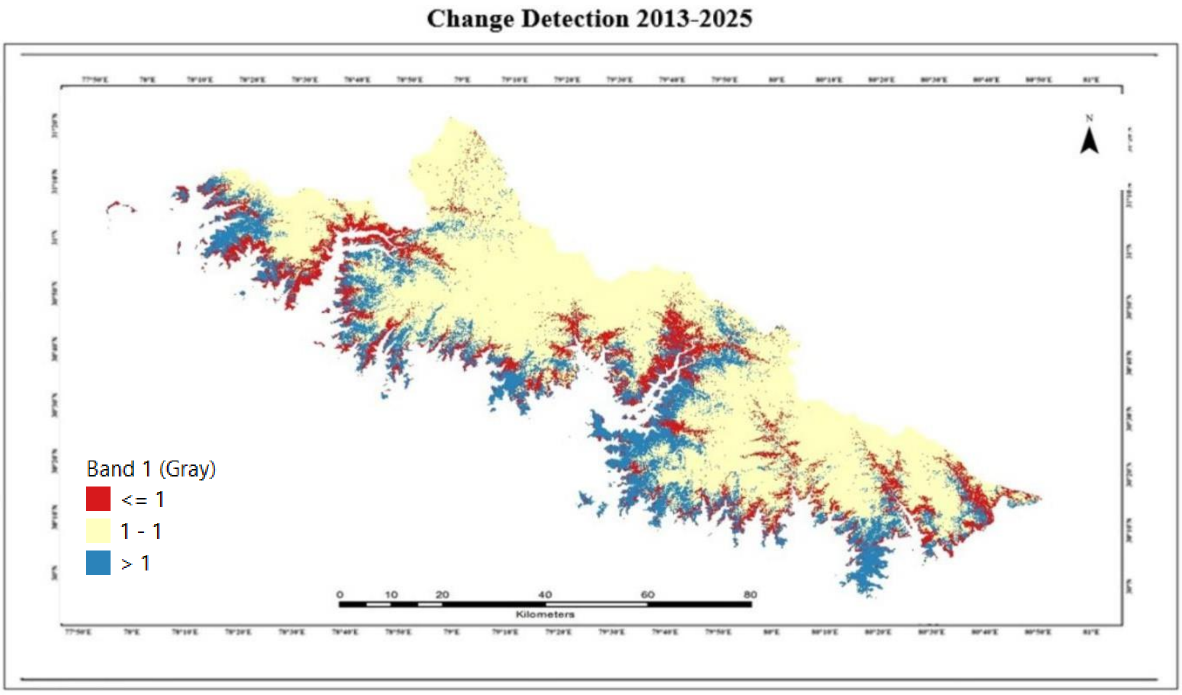

FIGURE 18 (CHANGE DETECTION 2013-2025)

5. Discussion

A wide-ranging spatiotemporal analysis of vegetation dynamics in the Western Himalayan region of Uttarakhand revealed considerable ecological developments associated with climate variability and shifting land use patterns based on NDVI values derived from high-resolution LISS-IV satellite images (2013-2025). From the observed vegetation trends, there is a picture of greening at a broad scale and spatially targeted stress, which reflects a complex ecological system response.

5.1 Decadal Vegetation Cover Dynamics and Trends

From 2013-2025, there was a consistent increase in NDVI across much of the landscape. Areas that were showing low or moderate NDVI values gradually exhibited greening throughout the period, particularly the mid-altitude belts (1500-3000m) where NDVI transitioned from ranges of 0.15-0.25 around 2013 to 0.35-0.45 and more in 2021, indicating rising vegetation productivity and increasing canopy density. By 2025, these trends had intensified, particularly in the areas with advantageous microclimates and less anthropogenic disturbance.

Historically, high-altitude sites above 4500 meters were evidently devoid of vegetation, covered in perpetual snow and ice, and barren land, until, by 2021, some evidence of vegetative activity began to emerge. Surfaces in deglaciated valleys and slopes reached NDVI values of 0.45+, in some locations by 2025, indicating a emergence of alpine vegetation. The spread of vegetation into areas that were earlier covered with snow and glaciers shows that these regions have become much warmer for a long time.

However, the pattern of vegetation increase was not uniform in space across the high-altitude landscapes. Locations that also experienced expansion of urban activity, more so, existed within low elevation and peri-urban settings, appeared to experience negative or negligible changes in NDVI, specifically along expanding road networks, in urban edges, and in cultivated land. This spatial variability explains the dynamic relationship between climate change adaptation taking place at high altitude, as opposed to degradation due to anthropogenic pressures taking place where humans reside in low elevation.

5.2 NDVI Cluster Analysis & Change Detection

Utilizing unsupervised KMeans clustering on average NDVI composites indicated three main classes of vegetation change during the study period. Between 2013 and 2017, most changes were minor and only in the lower valleys and coniferous forest patches. By 2021, mid-altitudinal areas began to shift into more NDVI classes, indicating a greater level of photosynthetic activity and accumulation of biomass.

Between 2017 and 2025, the pattern of clustering was significantly pronounced in that greening across the alpine and sub-alpine belt intensified. High altitude areas that had previously had NDVI values below 0.25 had moved into moderate or high NDVI clusters (0.35-0.55) indicating that a stable form, or vegetation is now established in previously non-vegetated areas. The 2025 clustering map supported this observation, as significant vegetative signatures were even present in areas that were above 3500 meters.

There were some areas that were unchanged or declined slightly with stable low NDVI clusters associated with barren lands, or other non-vegetated areas that were consistently snow-covered. These areas will need further field-based verification since it is not clear whether the causes are limited persistent abiotic factors, land degradation, or seasonal variability in snow. NDVI clustering and classified change maps indicated strong supporting evidence for a landscape-level ecosystem changes, which is in line with climate driven vegetation migration patterns documented in other high mountain systems.

5.3 Future Directions

The study will now evaluate year on year changes in the vegetation dynamics using LISS-4 data from 2010 until 2025 and also conduct a robust ground validation of the changes as well as build predictive model for vegetation change analysis.

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