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Original Research Article

Sustainable Management and Conservation of Shere Hills Forest Reserve Using Integrated GIS and Remote Sensing Techniques: A Multi-Temporal Analysis

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Abstract: Forest reserves are increasingly threatened by anthropogenic activities and climate-induced environmental change, necessitating robust geospatial techniques for effective monitoring and sustainable management. This study evaluated the long-term dynamics and conservation status of the Shere Hills Forest Reserve (SHFR), Plateau State, Nigeria, using an integrated Geographic Information System (GIS) and Remote Sensing framework. Multi-temporal Landsat imagery (1994, 2004, 2014, and 2024), high-resolution unmanned aerial vehicle (UAV) imagery, Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) data, and Differential Global Positioning System (DGPS) observations were integrated to assess land use/land cover (LULC) dynamics, vegetation condition, degradation patterns, and forest fragmentation. Random Forest Classification was applied for LULC mapping, while the Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), change detection, and landscape fragmentation metrics were used to quantify vegetation health and ecological integrity. Classification results demonstrated high reliability, with overall accuracies ranging from 84.8% to 92.8% and Kappa coefficients between 0.808 and 0.897. The analysis revealed substantial landscape transformation over the 30-year period, characterized by a 177% increase in built-up areas and a 29% decline in cropland, reflecting rapid urban expansion and changing land-use practices. In contrast, forest cover increased by 4.3%, accompanied by improvements in NDVI, VCI, core forest connectivity, and reduced edge density, indicating ecosystem resilience and progressive natural regeneration despite increasing anthropogenic pressure. These findings demonstrate the value of integrating GIS and Remote Sensing for long-term forest monitoring and provide a scientific basis for evidence-based conservation planning, biodiversity protection, and sustainable management of the Shere Hills Forest Reserve and similar montane forest ecosystems.

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Keywords: Forest Fragmentation, Change Detection, Random Forest Classification.

1.0 Introduction

1.1 Background and Context

Sustainable management and conservation are essential for maintaining the balance between human needs and environmental health. They involve a holistic approach that considers ecological, economic, and social dimensions (Tariq, 2026; Dodoo et al., 2025). Sustainable Forest Management aims to maintain and enhance the economic, social, and environmental values of all types of forests. It includes techniques such as afforestation, reforestation, selective logging, and prescribed burning to conserve biodiversity and respond to climate change. These strategies are crucial for ensuring a secure future for biodiversity and the well-being of future generations to balance human demands with preserving biodiversity and ecosystems (Abuh & Bello, 2025; Adaaja et al., 2024).

The Shere Hills Forest Reserve (SHFR), situated approximately 10km east of Jos city on the Jos Plateau (9° 51'N - 10° 00'N, 8° 54'E - 9° 06'E), represents one of Nigeria's most significant montane ecosystems, with an elevation of about 1,776m above sea level. As a designated forest reserve spanning between Jos East and Jos North Local Government Areas of Plateau State, Nigeria. The SHFR embodies a complex socio-ecological system where granitic inselbergs intersect with guinea savanna vegetation, sacred cultural sites, and intensifying anthropogenic pressures. Forests are tremendously endowed to sustain the health of the environment by regulating climate both at the regional and global levels. This unique and practicable remedy protects people and also creates a basis for more sustainable economic and social development. However, this natural mechanism is often hampered by human activities, which disrupt the atmospheric structure of the Earth.

2.0 Materials and Method

2.1 Study Area Description

The Shere Hills Forest Reserve (SHFR), situated approximately 10km east of Jos city on the Jos Plateau (9° 51'N - 10° 00'N, 8° 54'E - 9° 06'E), encompasses approximately 20, 200 hectares on the Jos Plateau, Nigeria. The terrain is characterized by rugged granitic outcrops, undulating highlands, and deeply incised valleys forming part of the basement complex geology. Elevation ranges from about 897m to 1,776m at the highest peak, creating vegetation zonation (Owolabi et al., 2021).

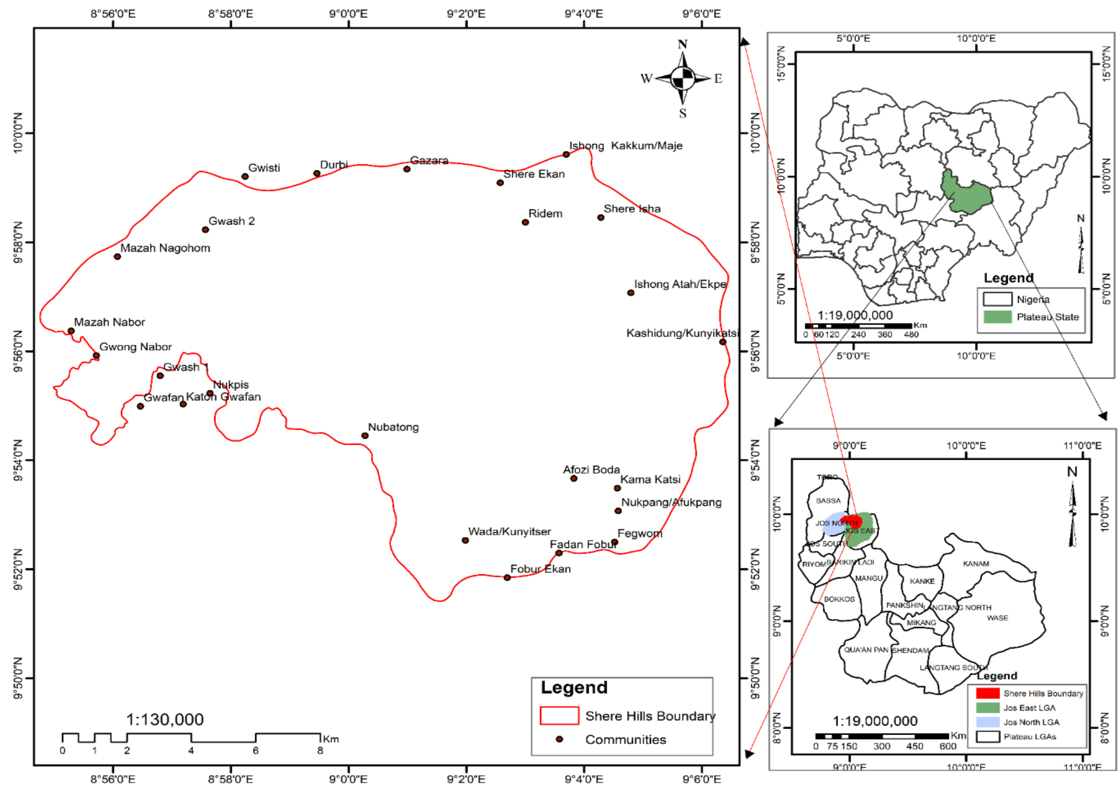

Figure 1: Map of Nigeria showing Plateau State and Shere Hills Forest Reserve (Source: GIS Analysis, 2025)

2.2 Data Sources and Specifications

Table 1: Data Specifications

Dataset	Sensor	Spatial Resolution	Temporal Coverage	Purpose
Drone imagery	DJI Mavic 3M	5cm GSD	Aug–Sep 2025	High-resolution patches, Base-layer & visual interpretation
Landsat-8 OLI	USGS	30 m	1994, 2004, 2014, 2024	LULC change detection
SRTM v3	NASA	30 m	2000	DEM, relief, drainage
DGPS	Hi-Target V30	≤1 m (DGPS)	Aug–Sep 2025	Ground control & validation

Note: Cloud constraint: All satellite scenes selected with <10 % cloud cover.

2.3 Image Processing

Satellite imagery underwent systematic preprocessing to ensure Radiometric consistency and geometric precision across the multi-temporal dataset. All Landsat and Sentinel-2 images were processed to a level-2 surface reflectance product.

Agisoft Metashape was also used to import the drone-captured RGB and multispectral images. The images were then aligned through the photo alignment process, where Metashape detects matching points between overlapping images to generate a sparse point cloud and estimate camera positions. After alignment, optimization of the camera alignment was carried out to ensure multispectral bans are properly calibrated and aligned. This include applying radiometric calibration using reflectance panel data to ensure accurate spectral values, then a dense point cloud was generated, which provides a detailed representation of the terrain and surface features.

2.3.1 Radiometric Calibration

Radiometric calibration converts digital numbers (DN) from sensor raw data into physically meaningful units such as radiance or reflectance. The following steps outline the standard procedure:

Step 1: Dark Current Subtraction (Bias Correction)

Remove the electronic offset and dark current noise from the raw digital numbers:

$$DNcorrected = DNraw - DNdark \quad (1)$$

where:

- DN_{raw} = Raw digital number from sensor
- DN_{dark} = Dark current measurement (obtained with closed shutter)

Step 2: Gain and Offset Application

Convert corrected DN values to at-sensor radiance using sensor-specific gain and offset coefficients:

$$L\lambda = Gain \times DNcorrected + Offset \quad (2)$$

where:

- L_λ = At-sensor spectral radiance ($W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1}$)
- $Gain$ = Radiometric gain coefficient (sensor-specific)
- $Offset$ = Radiometric offset coefficient (sensor-specific)

Step 3: Conversion to Top-of-Atmosphere (TOA) Reflectance

Convert radiance to unitless TOA reflectance to normalize for solar irradiance and geometry:

$$\rho_\lambda = \frac{\pi \cdot L_\lambda \cdot d^2}{ESUN_\lambda \cdot \cos(\theta_s)} \quad (3)$$

where:

- ρ_λ = TOA planetary reflectance (unitless, 0–1)
- d = Earth–Sun distance in astronomical units (AU)
- $ESUN_\lambda$ = Mean exo-atmospheric solar irradiance ($W \cdot m^{-2} \cdot \mu m^{-1}$) • θ_s = Solar zenith angle (degrees)

2.3.2 Atmospheric Correction

Removing atmospheric effects to obtain surface reflectance using methods such as:

- DOS (Dark Object Subtraction): Assumes zero reflectance for dark targets
- 6S/Second Simulation of Satellite Signal in the Solar Spectrum: Radiative Transfer Modelling
- FLAASH/MODTRAN: Moderate spectral atmospheric correction
- Sen2Cor/MAJA: Sensor-specific processors

The atmospheric correction equation given as:

$$\rho_{surface} = \frac{\rho_{TOA} - \rho_{atm}^{path}}{T_{atm} \cdot T_{solar}} \tag{4}$$

where T_{atm} and T_{solar} are atmospheric and solar transmittances, respectively.

2.3.3 Geometric Correction

Images were georeferenced to the Universal Transverse Mercator (UTM) projection, Zone 32N, WGS-84 datum, using 25 ground control points (GCPs) collected via Differential GPS. Root mean square error (RMSE) was maintained below 0.5pixels for all images.

2.4 Random Forest Classification

Land use/land cover classification was performed using the Random Forest (RF) machine learning algorithm, an ensemble method that constructs multiple decision trees during training and outputs a model of the classes for classification. The training data was first collected by selecting sample areas that represent known classes such as Vegetation, Water body, Built-up areas, Rockoutcrop or Crop land. These samples are used to train the model. The algorithm then builds multiple decision trees by randomly selecting subsets of the training data and input variables (such as spectral bands or vegetation indices). Each tree independently classifies the data, and the final output is determined by majority voting among all the trees, which improves accuracy and reduces overfitting.

2.5 Accuracy Assessment

Classification accuracy was evaluated using an independent validation dataset (n=450 points) collected during fieldwork and visual interpretation of high-resolution UAV imagery. The process begins by collecting reference (ground truth) data from field surveys and high-resolution imagery. These reference points were compared with the classified image to check whether each pixel has been assigned to the correct class, such as vegetation, water body, cropland, rock-outcrop or built-up area. The comparison is summarised in a table called a confusion matrix (error matrix). This matrix shows the relationship between the actual classes (reference data) and the predicted classes (classified image). From this matrix, several important accuracy metrics were derived.

2.5.1 Confusion Matrix

The error matrix M was constructed where element mij represents the number of validation pixels of class i classified as class j.

2.5.2 Overall Accuracy (OA)

$$OA = \frac{\sum_{i=1}^{k} mii}{N} \tag{6}$$

Where K = 5 is the number of classes, mii are diagonal elements (correct classifications), and N is the total number of validation samples

2.5.3 Kappa Coefficient (K)

The Cohen's Kappa statistics measured the agreement beyond chance:

$$K = \frac{N\sum_{i=1}^{k} mii - \sum_{i=1}^{k}(m_i + m_i)}{N^2 - \sum_{i=1}^{k}(mi+ .\ m+i)} \tag{7}$$

Where $mi+$ *and* $m+i$ are row and column marginal totals, respectively

2.6 Vegetation Analysis and Degradation Assessment

2.6.1 Normalized Vegetation Difference Index (NDVI)

Vegetation health and density were quantified using:

$$NDVI = \frac{\rho NIR - \rho Red}{\rho NIR + \rho Red} \tag{8}$$

Where ρNIR *and* ρRed are reflectance in near-infrared and red bands, respectively.

NDVI ranges from -1 (water/shadow) to +1 (dense vegetation)

2.6.2 Degradation Hotspot Mapping

Degradation Hotspot Mapping is a geospatial analysis process used to identify and locate areas experiencing significant environmental degradation, such as deforestation, soil erosion, vegetation loss, or land deterioration. It helps highlight zones where environmental conditions are declining most rapidly so that targeted interventions can be planned. Relevant indicators of degradation were derived, these include vegetation indices (NDVI) to detect vegetation loss, land use/land cover change analysis to identify deforestation or urban expansion and terrain analysis (slope and elevation) to assess erosion risk. Multiple indicators were combined to provide a more comprehensive assessment of degradation. The result is visualized as a degradation hotspot map, where areas are categorized into levels such as low. Moderate and high degradation.

2.7 Change Detection Analysis

The change detection is a geospatial technique used to identify changes in land use, land cover or environmental conditions over time by comparing satellite images from different dates. After the image preprocessing, classification was performed on each image separately using Random Forest methods classification in the ArcGIS software. Each image was categorized into classes such as vegetation, water body, built-up areas, rock-outcrop and crop land. The classified images were then compared using image differencing techniques. This step helps to identify areas where significant changes have occurred between the different time periods (1994-2024). The results are presented as change maps, statistical tables, and graphs showing the magnitude, type and spatial distribution of changes.

2.8 Landscape Fragmentation Analysis.

Forest Fragmentation is the process by which a large, continuous forest area is broken into smaller and isolated patches due to natural or human activities such as agriculture, urbanization, road construction, logging, mining, and infrastructure development. It is important for understanding habitat loss, biodiversity decline, and environmental sustainability. The produced land cover map was analysed using fragmentation metrics. These metrics include patch size, patch density, edge density, shape index, and connectivity, which describe how fragmented or continuous the forest is. The analysis then evaluates spatial patterns by identifying areas where large continuous habitats have been divided into smaller patches, increasing isolation between them, the results are then presented as maps and statistical outputs showing levels of fragmentation across the Shere Hills.

3.0 Results

3.1 Classification Accuracy

Table 2: Classification Accuracy Summary

Year	Overall Accuracy (OA %)	Target OA (%)	Kappa Coefficient (K)
1994	84.8	85.0	0.8079
2004	86.6	87.0	0.8334
2014	84.8	85.0	0.8079
2024	92.8	92.0	0.8973

The Random Forest classification achieved high accuracy across all years (Table 1). Overall accuracy ranged from 84.8% to 91.8%, with Kappa coefficients between 0.808 and 0.897: classified as "Almost Perfect" agreement (Landis & Koch, 1977). The highest accuracy was recorded in 2024 (OA = 91.8%, Kappa = 0.897), attributable to improved image quality and training data.

3.2 Land Use/Land Cover Dynamics (1994-2024)

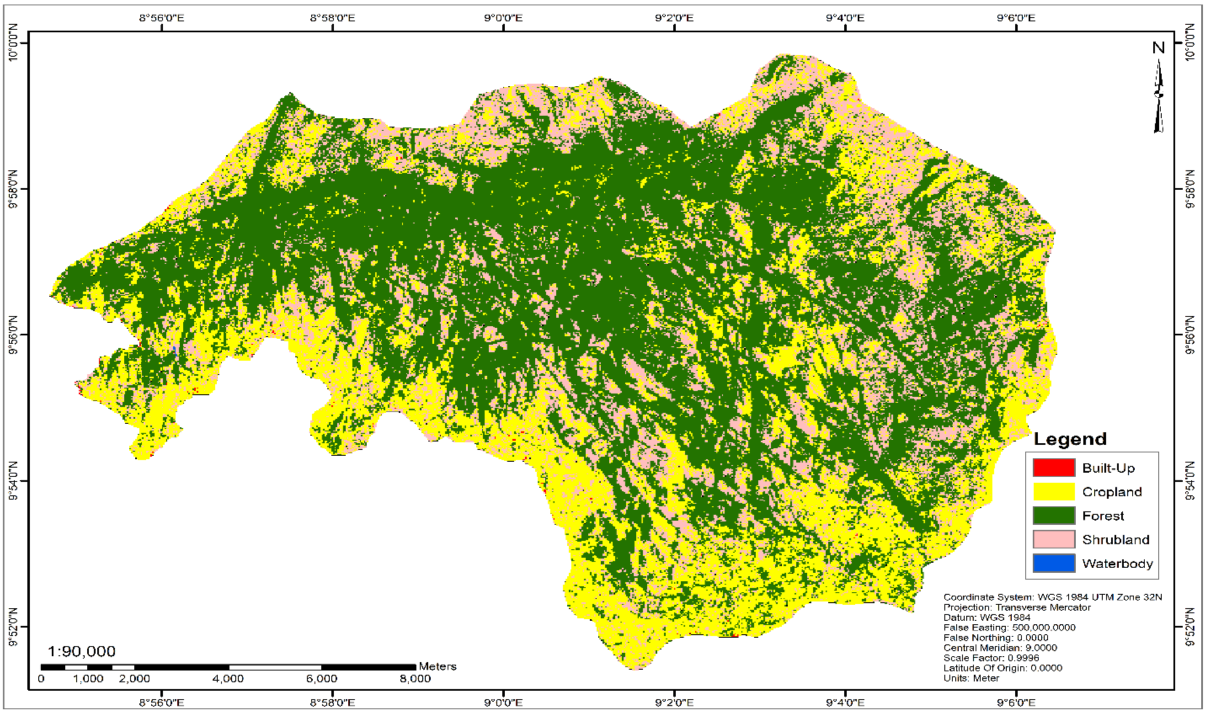

Figure 2: Land use and Land cover map of Shere Hill, 1994
(Source: GIS Analysis, 2026)

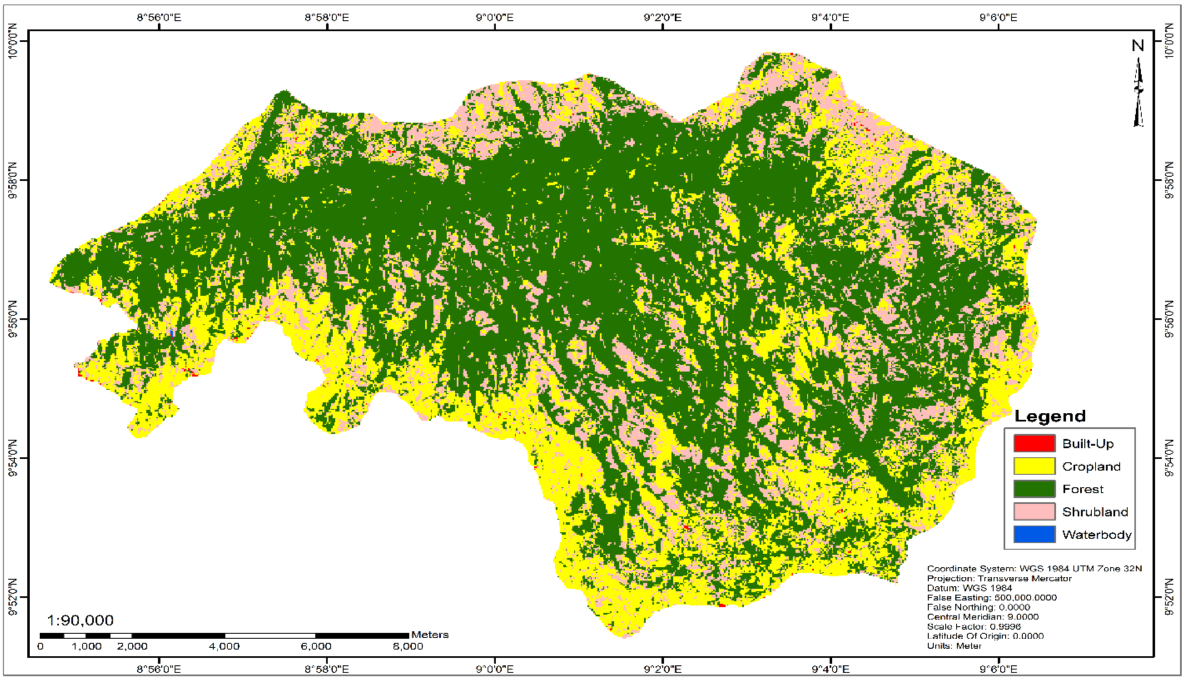

Figure 3: Land use and Land cover map of Shere Hill 2004
(Source: GIS Analysis, 2026)

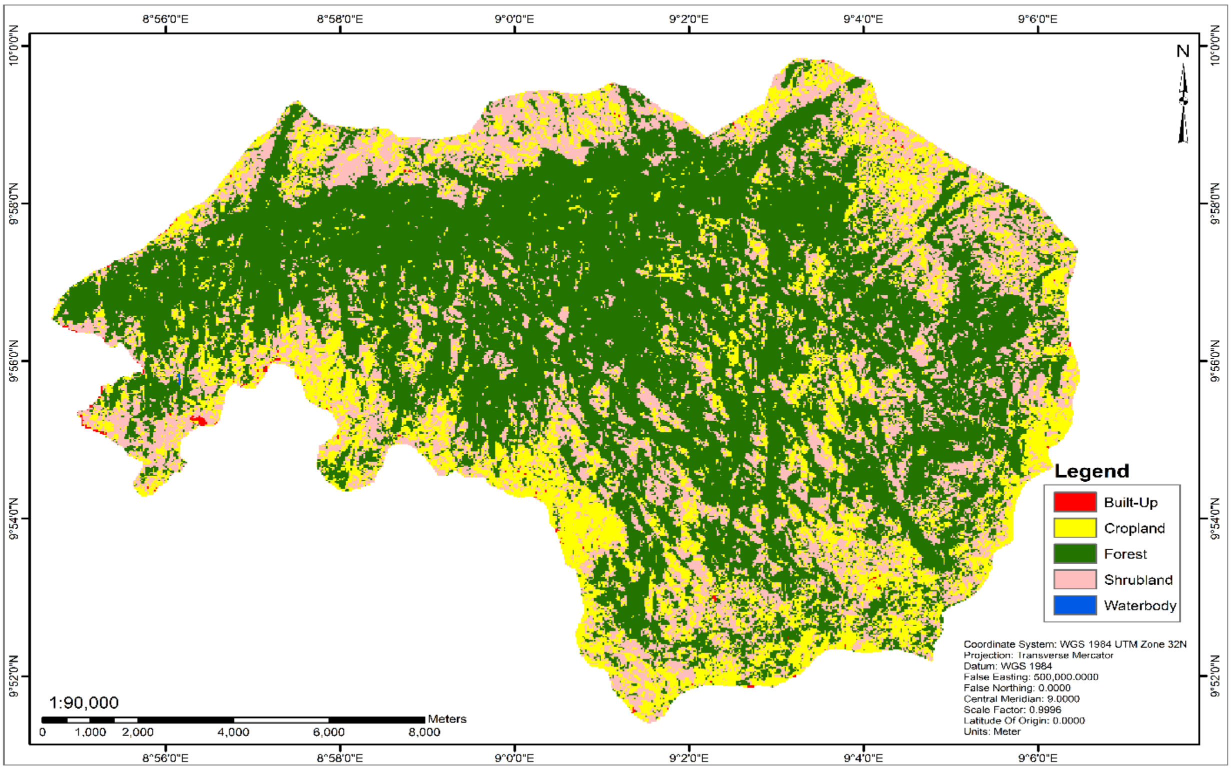

Figure 4: Land use and Land cover map of Shere Hill 2014
(Source: GIS Analysis, 2026)

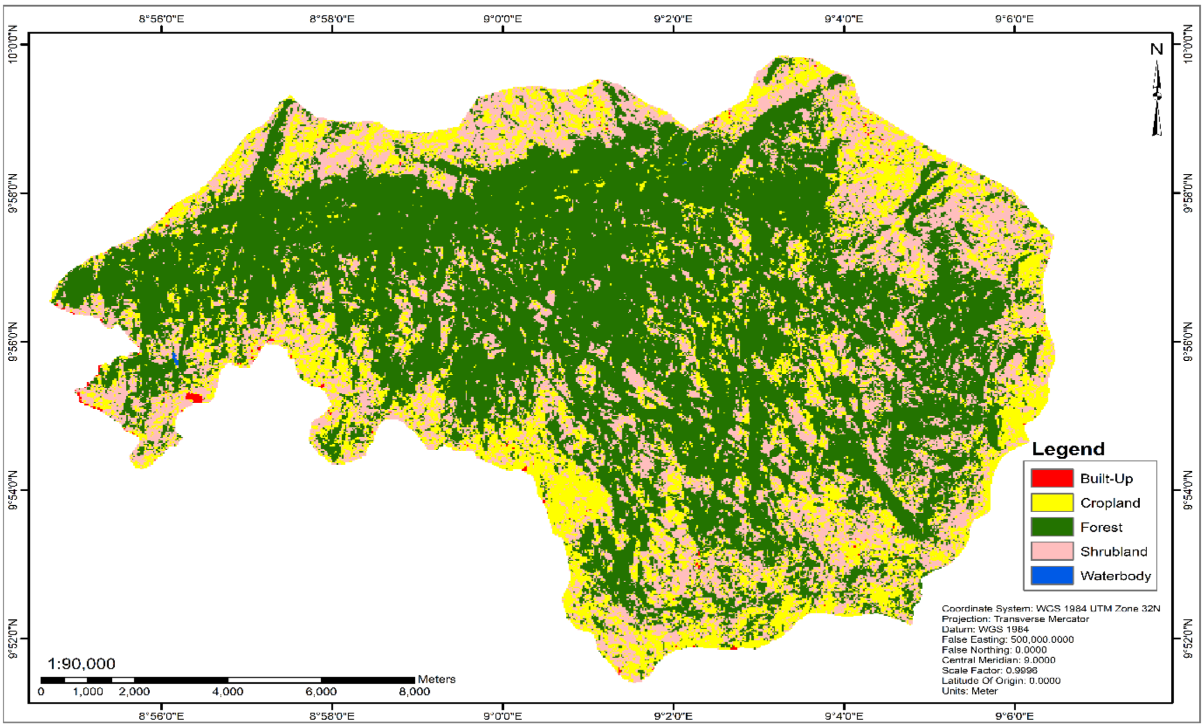

Figure 5: Land use and Land cover map of Shere Hill 2024
(Source: GIS Analysis, 2026)

Over the 30-year study period, significant landscape transformations occurred (Table 3). Built-up areas expanded dramatically by 177% (from 12 ha to 33 ha; +3.45%/year), driven by urban sprawl from Jos city, located 10 km west of the reserve. Conversely, cropland declined by 29% (from 5,084 ha to 3,608 ha; −1.14%/year), while shrubland increased by 25% (from 3,992 ha to 4,999 ha; +0.75%/year), suggesting agricultural abandonment followed by natural regeneration.

Notably, forest cover increased by 4.3% (from 10,602 ha to 11,061 ha; +0.14%/year), a counterintuitive finding given concurrent urbanization. This indicates that forest recovery and urban expansion are occurring in different landscape compartments, rather than being mutually exclusive. The period 2004–2014 exhibited the highest change intensity (51.4% of the landscape changed), coinciding with socio-economic transitions in Plateau State.

Urban encroachment was concentrated within 500 m of the reserve boundary, where built-up area increased from 10 ha (0.05%) in 1994 to 28 ha (0.14%) in 2024, 177% increase, underscoring the need for proactive management of the urban interface zone.

Table 3: Land Use/Land Cover Change Summary (1994-2024)

Class	1994 (ha)	2024 (ha)	Net Change	Change (%)	Annual Rate
Built-up	12	33	+21	+177%	+3.45%/yr
Cropland	5,084	3,608	−1,476	−29%	−1.14%/yr
Forest	10,602	11,061	+459	+4.3%	+0.14%/yr
Shrubland	3,992	4,999	+1,008	+25%	+0.75%/yr

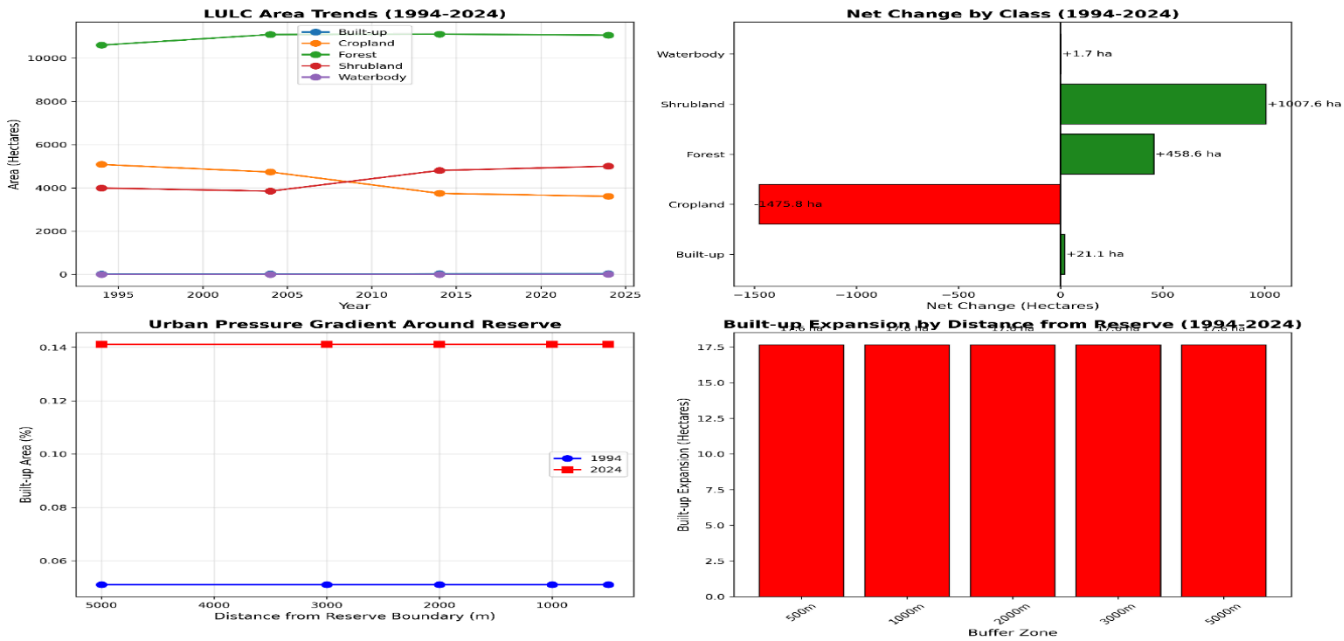

Figure 6: Change Detection Graph of Shere Hill
(Source: GIS Analysis, 2026)

3.3 Vegetation Dynamics and Degradation Recovery

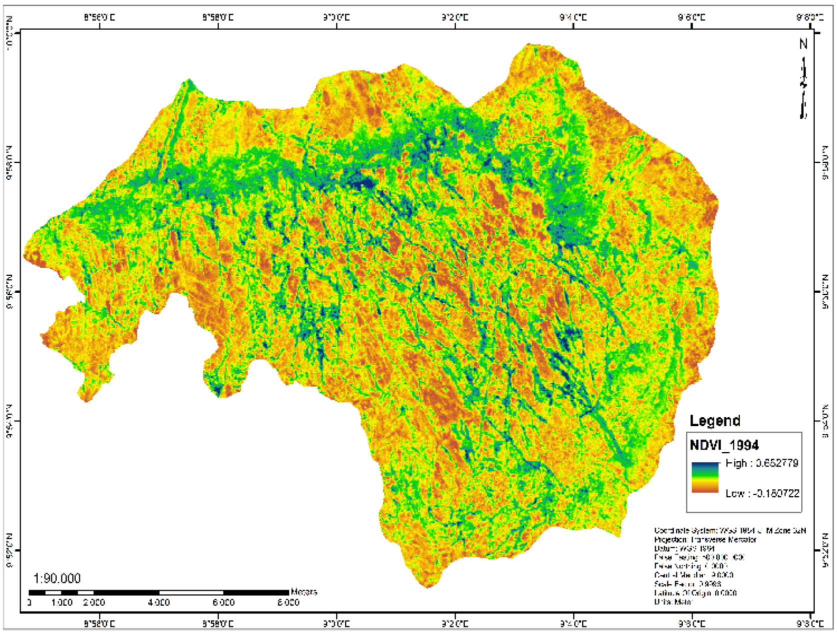

Figure 7a: NDVI 1994

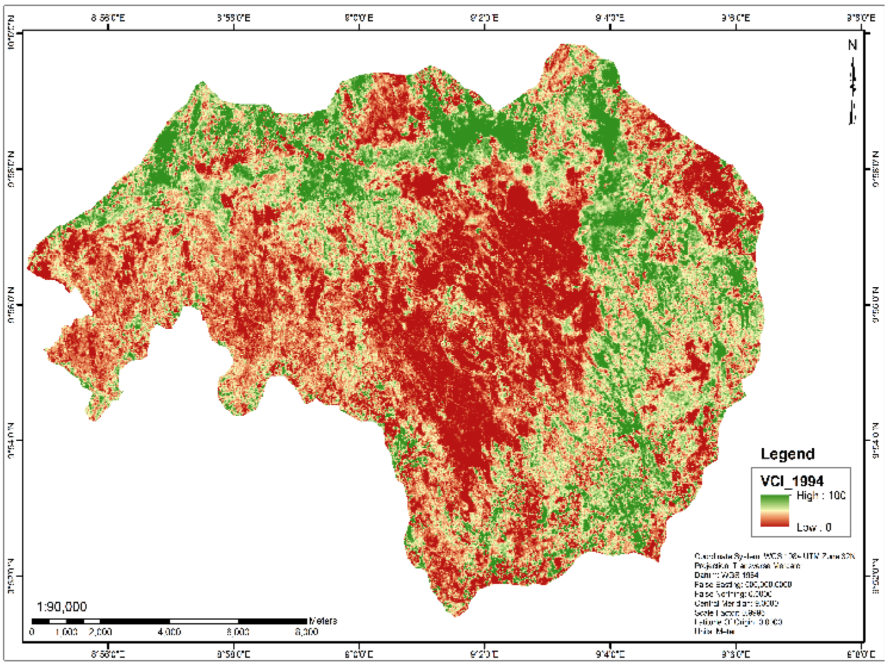

Figure 7b: VCI 1994

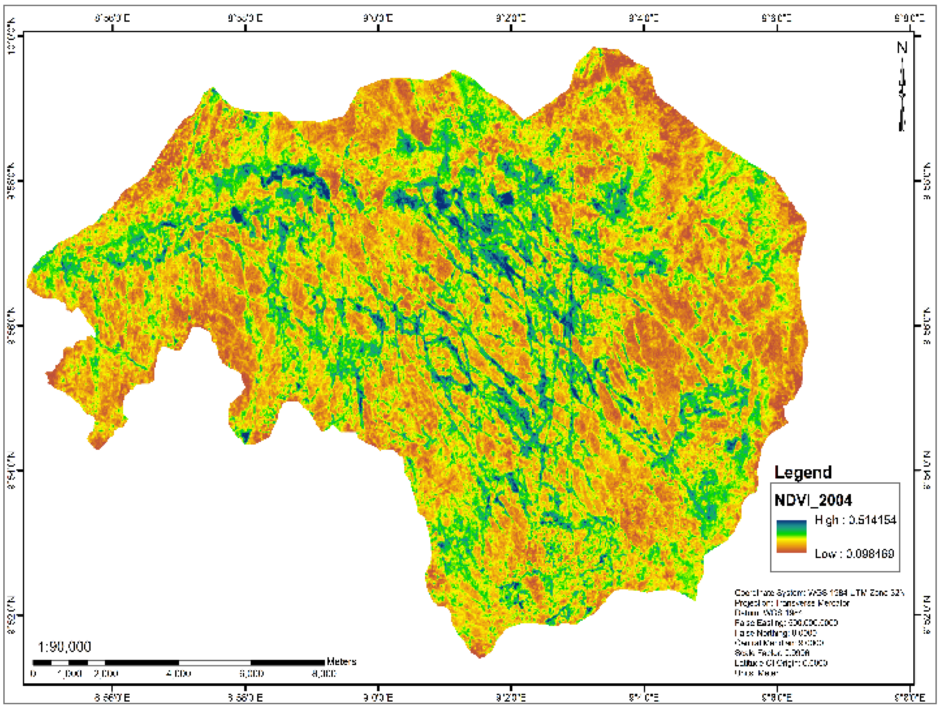

Figure 8a: NDVI 2004

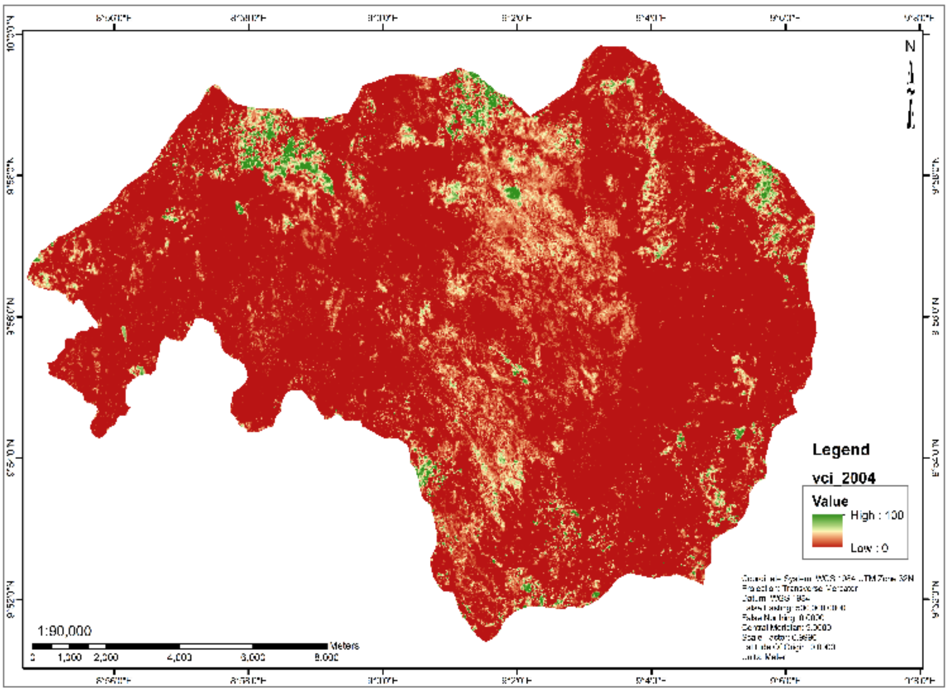

Figure 8b: VCI 2004

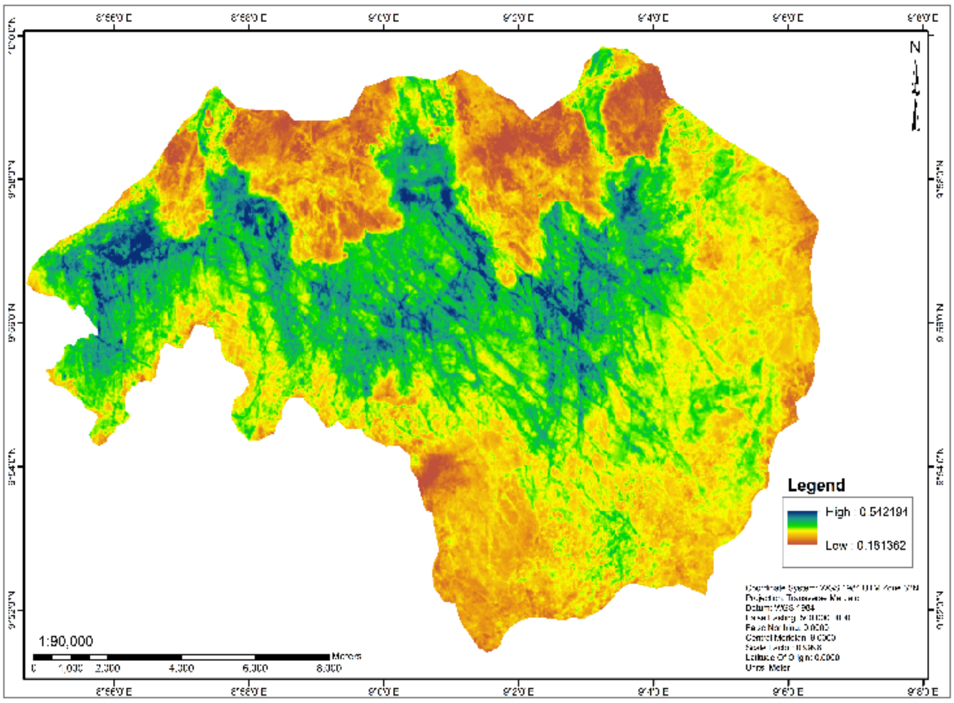

Figure 9a: NDVI 2014

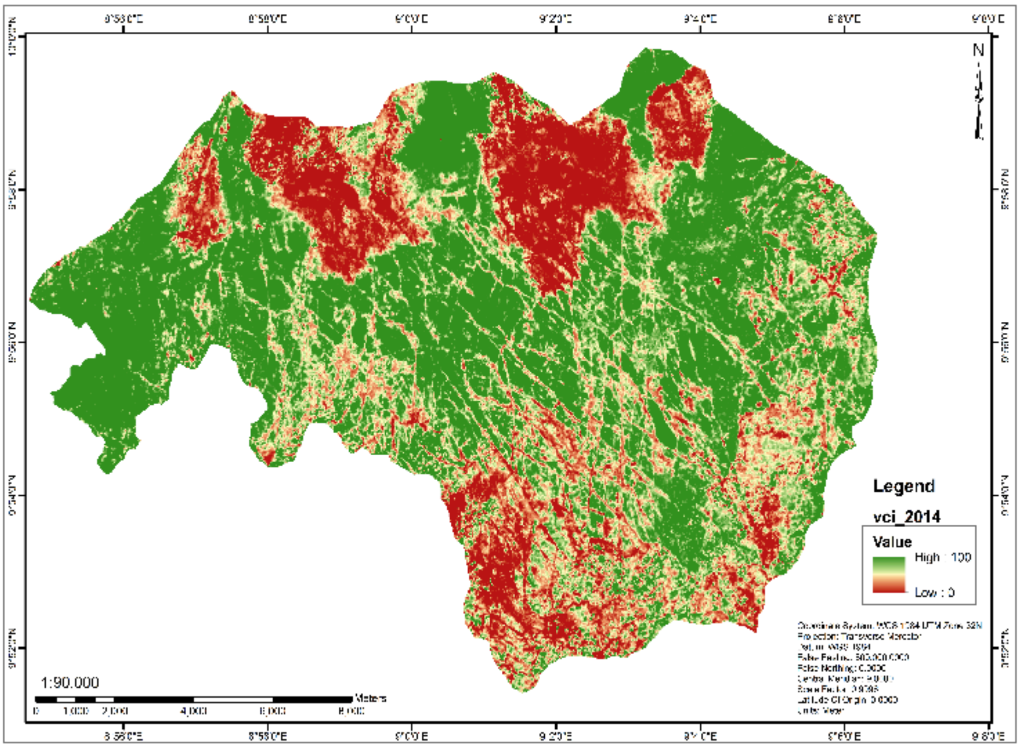

Figure 9b: VCI 2014

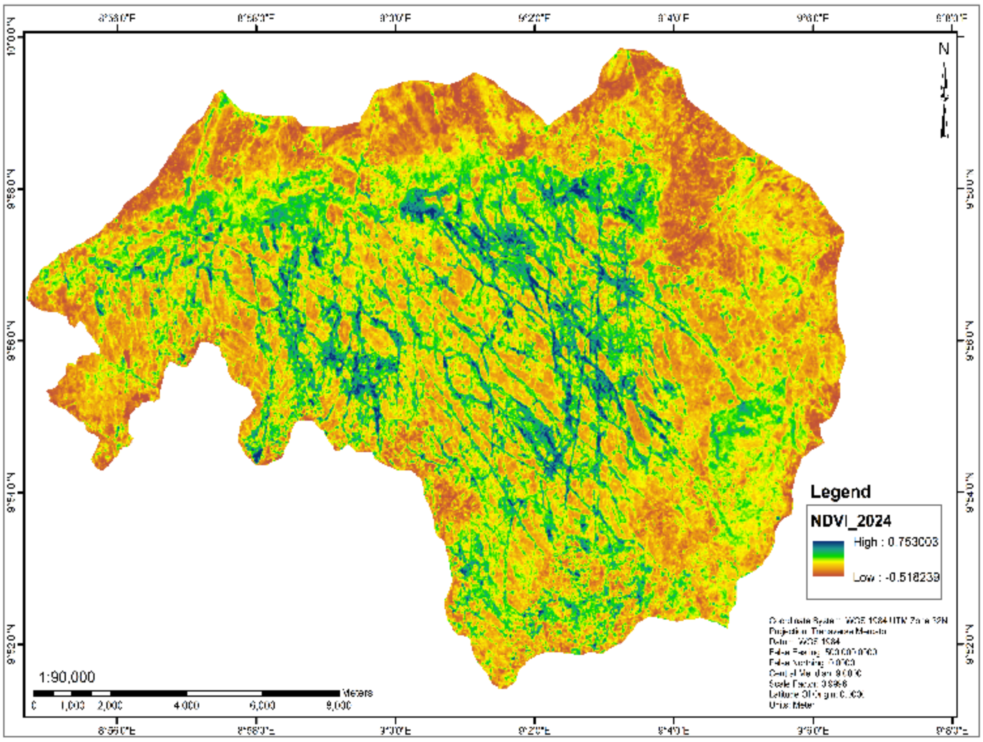

Figure 10a: NDVI 2024

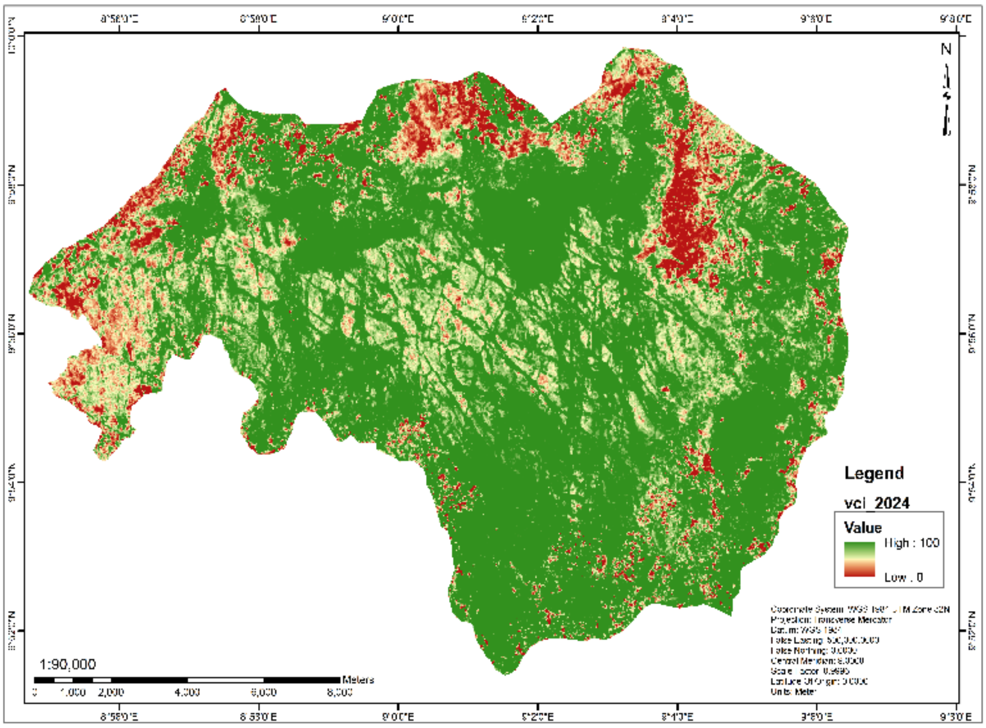

Figure 10b: VCI 2024

The NDVI and VCI analyses reveal a compelling recovery story following a severe degradation event (Table 4). Mean NDVI increased from 0.295 in 1994 to 0.352 in 2024 (+19%), while the Vegetation Condition Index (VCI) improved dramatically from 40 to 81 (+103%).

A critical degradation event occurred in 2004 (NDVI = 0.256; VCI = 7), where 95% of the reserve experienced severe vegetation stress. This anomaly likely resulted from drought conditions across the Sahelian zone, combined with land use pressure (51.4% change intensity during 2004–2014). However, the subsequent recovery (2014–2024) demonstrates the resilience of this montane ecosystem. Severely stressed vegetation (VCI < 40%) decreased from 55% in 1994 to only 11% in 2024, while healthy vegetation (VCI > 60%) increased from 27% to 79%. This recovery pattern suggests that natural regeneration is a cost-effective restoration strategy when disturbance pressures are reduced, consistent with global reforestation literature (Chazdon et al., 2016).

Table 4: NDVI Statistics Summary

Year	Mean NDVI	Median NDVI	Std Dev	Min NDVI	Max NDVI	5TH Percentile	95th Percentile	Veg Health
1994	0.2954	0.2893	0.062	-0.1807	0.6528	0.2045	0.4049	Poor
2004	0.2559	0.2486	0.049	0.0985	0.5142	0.1864	0.3472	Poor
2014	0.3277	0.3216	0.056	0.1814	0.5422	0.2406	0.4255	Fair
2024	0.3524	0.3392	0.0852	-0.5182	0.753	0.2337	0.5142	Fair

Table 5: NDVI Anomalies Summary

Year	Mean NDVI	Anomaly	Anomaly (%)	Classification
1994	0.29536	-0.01248	-4.05292	Normal
2004	0.25590	-0.05194	-16.87182	Moderate Degradation
2014	0.32766	0.01983	6.44067	Normal
2024	0.35242	0.04459	14.48411	Moderate Greening

Table 6: Vegetation Condition Index (VCI) Summary

Year	Mean VCI	Healthy (%)	Severe Stress (%)
1994	40	27%	55%
2004	7	2%	95%
2014	65	59%	28%
2024	81	79%	11%

3.4 Forest Fragmentation

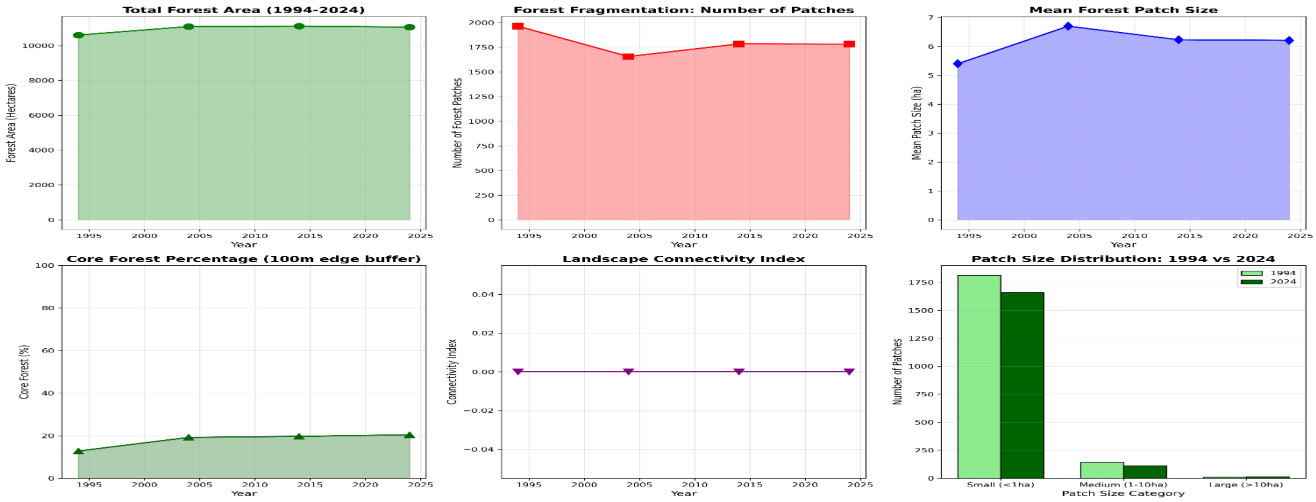

Figure 11: Forest Fragmentation Graph of Shere Hill

Table 7: Forest Fragmentation Metrics

Metric	1994	2004	2014	2024
Total Forest (ha)	10,602	11,093	11,113	11,061
Number of Patches	1,965	1,657	1,785	1,783
Core Forest (%)	12.8%	19.2%	19.7%	20.4%
Edge Density (m/ha)	129	113	111	108

Forest fragmentation analysis revealed a nuanced pattern (Table 7). While the number of patches remained stable (~1,700–1,900), core forest (>100 m from edge) increased from 1,359 ha (12.8%) to 2,252 ha (20.4%) a 7.6 percentage point improvement. Edge density declined from 129 to 108 m/ha, indicating patches became more compact.

This apparent paradox (stable patch count but increasing core area) is explained by: (1) agricultural abandonment adjacent to existing forest, converting edge to core; (2) natural succession of shrubland to forest, expanding patch boundaries; and (3) decreasing edge effects as patches coalesce. The largest patch index remained high (91–93%), indicating a single contiguous forest block dominates the landscape critical for biodiversity conservation, supporting interior forest specialists.

4.0 Recommendations and Limitations

4.1 Recommendation:

Based on the findings, the following forest management and conservation recommendations are proposed:

- Strict Protection (8,272 ha): Maintain status, establish monitoring plots, implement fire management.

- Sustainable Management (2,776 ha): Community agreements, ecotourism, controlled grazing.
- Urban Interface (1,238 ha): Firebreaks, buffer planting, signage, and encroachment monitoring.

4.2 Limitations and Mitigation

Limitation: Landsat 30m resolution, 2014 LST cloud contamination, No fire history data available and single-season imagery

Mitigation: 450 validation points minimize classification error, exclude from warming trend analysis, Inferred from NDVI anomaly patterns and Consistent dry-season acquisition across all years.

5.0 Conclusion

The integration of GIS and Remote Sensing techniques proved highly effective for monitoring environmental changes and assessing the conservation status of the Shere Hills forest reserve over a 30-year period. The study revealed that despite increasing urban expansion around the reserve, the forest ecosystem has demonstrated considerable resilience through gradual vegetation recovery, increased forest cover, and improved core forest connectivity. The application of Random Forest Classification, NDVI, VCI and fragmentation metrics provided reliable and detailed insights into land use dynamics, vegetation health, degradation hotspots and ecological recovery patterns. The findings highlight the importance of continuous monitoring, controlled land use practices, community-based conservation strategies, and sustainable management interventions to protect the ecological integrity of the reserve. Furthermore, the study emphasizes the role of geospatial technologies as cost-effective and efficient tools for supporting environmental management, biodiversity conservation, and evidence-based decision-making. Sustainable conservation policies, combined with proactive management of urban interface zones and restoration initiatives, are essential to ensure the long-term preservation of the Shere Hilla forest reserve for future generations.

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