

Assessing Spatio-Temporal Patterns of Deforestation in Nagaland for 2014–2024 Using Geospatial Techniques

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Abstract: This study investigates the spatio-temporal dynamics of deforestation in Nagaland, India, over a decade (2014–2024) using geospatial techniques such as satellite-based remote sensing, Normalized Difference Vegetation Index (NDVI) computation, and change detection analysis. Situated in the ecologically sensitive belt of Northeast India, Nagaland has experienced accelerating landscape modification due to anthropogenic and environmental pressures. The study aims to quantify forest-cover transitions, evaluate vegetation health, identify deforestation hotspots, and explore correlations with topography and population density. Multi-temporal Landsat 8 (2014) and Landsat 9 (2024) imagery were classified through supervised classification (Maximum Likelihood Algorithm) into six land-use/land-cover (LULC) categories—dense forest, open forest, scrub, agriculture, built-up area, and water bodies. NDVI was computed to assess vegetation vigor and spatial health, while post-classification comparison and NDVI differencing were employed for change detection. The analysis reveals a 10.6% decline in dense forest cover (−806 km²) alongside substantial increases in open forest (+8.6%), scrubland (+24.2%), and built-up area (+42.9%). NDVI values decreased from 0.58 to 0.47, indicating a deterioration in canopy density and photosynthetic activity. Deforestation hotspots were predominantly located in Dimapur, Mon, and Tuensang, regions of high population density and infrastructural expansion. Statistical correlation confirmed a strong positive relationship ($r = +0.81$) between population density and forest loss, while elevation exhibited an inverse association. The study interprets deforestation as a spatial–ecological process characterized by feedback loops between socio-economic development and environmental degradation. The transition from dense forest to open and degraded vegetation signifies a loss of ecosystem resilience, carbon storage capacity, and biodiversity connectivity. Ecological implications include increased soil erosion, hydrological imbalance, and reduced carbon sequestration potential (estimated at 40–45 Mt CO₂e). Socio-economically, forest depletion has intensified livelihood insecurity, particularly among indigenous and agrarian communities reliant on shifting cultivation (*jhum*). Policy recommendations emphasize geospatial monitoring, community-based forest governance, and slope-based land-use zoning to restore ecological balance. Integration of remote sensing technologies with participatory management frameworks is proposed to enhance adaptive governance and align with national forest and climate commitments (REDD+ and NDCs). The study contributes both methodologically and conceptually to the regional discourse on sustainable mountain forest management by demonstrating how deforestation in Nagaland embodies an ongoing forest transition without equilibrium. It underscores the urgency of reimagining forest conservation through a spatially intelligent and socially inclusive approach.

IndexTerms - Spatio-Temporal Pattern, Deforestation, Geospatial Techniques

1. INTRODUCTION

1.1 Background of the Study

Forests fulfil a multitude of ecological, hydrological, and socio-economic functions that span beyond timber provision—they contribute to carbon sequestration, biodiversity maintenance, watershed protection, and cultural livelihoods. In recent decades, however, the world's forested landscapes have increasingly been subject to conversion, fragmentation, and degradation, which has intensified the urgency of systematically monitoring and managing forest ecosystems. For example, analysis of remote-sensing data shows persistent vegetation degradation globally, with tropical forest systems in particular showing alarming emissions of carbon when lost or disturbed (Sur et al., 2024). Within the Indian context, forested land remains vital to rural livelihoods and environmental stability. The Forest Survey of India reports that forest and tree cover in India is approximately 21 % of the country's geographical area, against a policy target of 33 %. (UP42 blog, 2021). Such a gap reflects both developmental pressures and conservation challenges. Moreover, the rise in availability and resolution of satellite data has transformed forest monitoring,

allowing systematic tracking of changes over large spatial extents and long temporal spans (Gorelick et al., 2017). In elaborating the background for the present study, it is important to situate three inter-linked elements:

1. **Spatial heterogeneity of forests:** Nagaland sits within the Eastern Himalayas biodiversity hotspot and features a mosaic of forest types from evergreen wet hill forests to bamboo-dominated sections and secondary regrowth zones. This variety complicates change-detection efforts because forest class definitions, phenology, and canopy structure vary markedly.
2. **Temporal dimension:** The decade from 2014 to 2024 spans considerable developmental and environmental change: policy shifts, increased infrastructural investment, climate-induced stressors, and evolving land-use practices. Tracking change across this timeframe offers both a recent and relevant window for detecting deforestation patterns.
3. **Methodological advances:** The availability of freely accessible satellite archives (e.g., Landsat), advanced classification algorithms, and high-performance computing in platforms like Google Earth Engine has democratized robust monitoring. Integrating supervised LULC classification with NDVI trend analysis strengthens inference on vegetative health and forest cover change (Singha et al., 2024).

This study specifically aims to contribute to the existing scholarly discourse by (a) applying multi-temporal remote-sensing data to the understudied Nagaland region; (b) combining LULC classification with NDVI analysis to capture both categorical change and vegetative health dynamics; and (c) focusing on a 10-year window (2014–2024) that includes recent changes often omitted in earlier studies. The incorporation of supervised classification, accuracy assessment, and change-detection methods further strengthens methodological rigour, and the temporal trajectory (how change unfolds) thereby underpinning efforts to guide sustainable forest and land-use governance.

1.2 PROBLEM STATEMENT

The growing rate of deforestation and forest degradation in Nagaland represents a complex environmental challenge that threatens both ecological stability and socio-economic resilience. Although forested landscapes continue to occupy a substantial share of the state's geography, recent spatio-temporal analyses indicate a steady decline in dense forest areas over the past decade, largely replaced by agricultural and built-up land uses (Guria et al., 2024; Jamir & Singh, 2020). The inadequacy of consistent, high-resolution datasets and systematic monitoring mechanisms has constrained the understanding of where, when, and how such changes occur. Most available datasets, including national forest inventories, provide only coarse decadal updates, masking localized variations in vegetation health and canopy density (Roy et al., 2021).

1.3 RESEARCH QUESTIONS

The formulation of research questions provides a structured pathway for examining the multidimensional phenomenon of deforestation in Nagaland through geospatial methodologies. This study operates on the premise that forest loss is not a static or uniform process but a temporally dynamic and spatially heterogeneous event influenced by environmental, socio-economic, and anthropogenic factors (Roy et al., 2021; Attri & Pathania, 2024). Therefore, to address the central aim of assessing spatio-temporal forest cover changes between 2014 and 2024, the following research questions are constructed to guide empirical investigation and analytical interpretation.

RQ1. What are the spatial patterns of deforestation and land-use/land-cover (LULC) transitions in Nagaland between 2014 and 2024?

The first research question seeks to determine the extent, distribution, and direction of forest cover change across the state. Understanding these spatial patterns is essential to identify zones experiencing acute deforestation, fragmentation, or regrowth. Remote sensing, through multi-temporal satellite imagery (e.g., Landsat 8 and 9), enables the mapping of transitions between classes such as dense forest, open forest, scrubland, agriculture, and built-up areas (Guria et al., 2024). This question underlines the need for a classification framework that can differentiate between genuine forest loss and seasonal or spectral variations, ensuring spatial precision in mapping forest transitions (Jamir & Singh, 2020).

RQ2. How has vegetation health, as represented by the Normalized Difference Vegetation Index (NDVI), changed during the 2014–2024 decade?

The second question extends beyond categorical land-use analysis to examine the physiological condition of vegetation. NDVI, derived from the near-infrared (NIR) and red (RED) reflectance bands, provides a quantitative indicator of vegetation vigor and chlorophyll density (Huete, 2012; Tucker et al., 2018). The index is computed using the formula:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

RQ3. WHAT ARE THE KEY DRIVERS INFLUENCING DEFORESTATION AND VEGETATION DEGRADATION IN NAGALAND?

Understanding deforestation requires correlating spatial evidence with underlying drivers. This question investigates anthropogenic, demographic, and environmental factors contributing to forest loss, such as shifting cultivation, road expansion, population growth, and urbanization (*Hiese et al., 2020; Lalnunzira & Pachuau, 2022*). It also considers climatic influences, including erratic rainfall patterns and temperature variations that may exacerbate vegetation stress. This dimension bridges geospatial analysis with socio-economic inquiry, offering insight into how human activity patterns correspond to spatial deforestation trends (*Singh et al., 2022*).

1.4 OBJECTIVES OF THE STUDY

Scientific evaluation of deforestation and vegetation dynamics in ecologically sensitive regions such as Nagaland necessitates a structured set of research objectives that combine spatial analysis, temporal assessment, and interpretive synthesis. The overarching goal of this study is to analyze the spatio-temporal patterns of deforestation in Nagaland during the period 2014–2024 using geospatial techniques, integrating remote sensing, land-use/land-cover (LULC) classification, and vegetation index-based approaches.

OBJECTIVE 1: TO CLASSIFY AND MAP THE LAND USE/LAND COVER (LULC) OF NAGALAND FOR THE YEARS 2014 AND 2024 USING LANDSAT IMAGERY.

The primary objective centers on producing accurate LULC maps for two benchmark years—2014 and 2024—by utilizing medium-resolution multispectral satellite data (Landsat 8 OLI for 2014 and Landsat 9 OLI for 2024). Through supervised classification methods, particularly the Maximum Likelihood Algorithm, major land-cover classes such as dense forest, open forest, scrubland, agricultural area, built-up area, and water bodies will be delineated (*Roy et al., 2021; Jamir & Singh, 2020*).

OBJECTIVE 2: TO COMPUTE AND EVALUATE THE NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI) FOR 2014 AND 2024 TO ASSESS VEGETATION HEALTH AND DENSITY.

The third objective addresses the qualitative aspect of vegetation change by employing NDVI as a proxy for chlorophyll abundance and canopy vigor. NDVI is calculated using the formula:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

OBJECTIVE 3: TO IDENTIFY AND DELINEATE DEFORESTATION HOTSPOTS USING CHANGE-DETECTION AND NDVI CORRELATION TECHNIQUES.

This objective seeks to spatially localize regions undergoing rapid or sustained deforestation by combining results from LULC change analysis and NDVI differentials. The approach involves overlaying NDVI decline zones with forest-to-non-forest transition pixels to isolate high-risk areas (*Guria et al., 2024*).

OBJECTIVE 4: TO EXAMINE THE RELATIONSHIP BETWEEN ANTHROPOGENIC DRIVERS AND OBSERVED DEFORESTATION TRENDS IN NAGALAND.

Understanding forest loss requires correlating spatial data with socio-economic indicators. This objective involves qualitative and spatial correlation analysis between deforestation patterns and drivers such as population density, agricultural expansion, and infrastructural development (*Lalnunzira & Pachuau, 2022*).

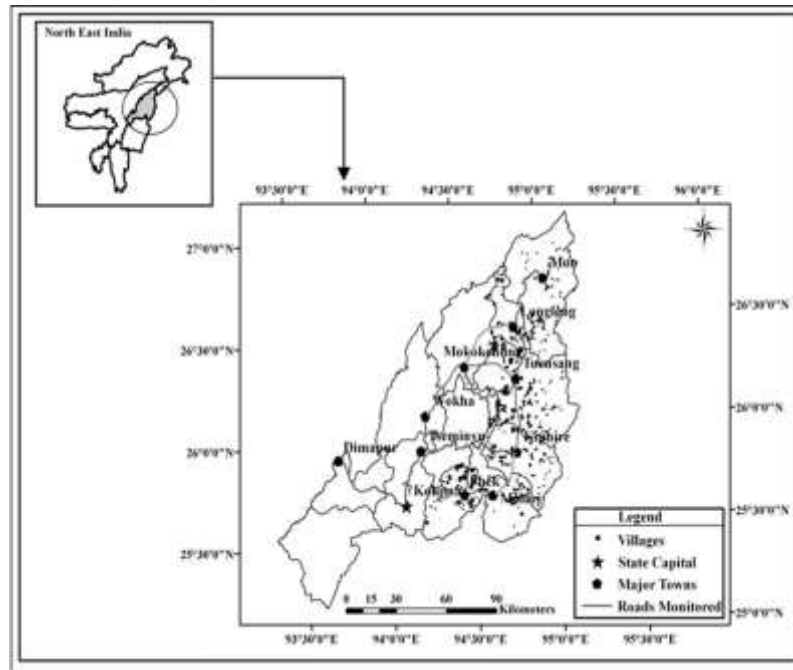
1.5 SIGNIFICANCE OF THE STUDY

The ecological and policy significance of assessing deforestation in Nagaland lies in its capacity to bridge scientific understanding with sustainable forest management. Forest ecosystems in Nagaland perform critical ecological services including soil stabilization, carbon sequestration, water regulation, and biodiversity conservation. Yet, these systems face mounting anthropogenic pressures arising from population growth, shifting cultivation, and developmental expansion. The study's significance thus emerges from its integration of spatial analytics, temporal assessment, and vegetation health evaluation, which collectively provide a multidimensional understanding of forest dynamics. By applying remote sensing and geospatial technologies, this research moves beyond traditional descriptive forest inventories, offering quantitative, replicable, and spatially explicit evidence on forest loss and degradation (*Roy et al., 2021; Guria et al., 2024*).

1.6 STUDY AREA DESCRIPTION

Nagaland, located in the northeastern region of India, is a mountainous state characterized by a rich mosaic of forests, shifting cultivation fields, and agro-ecosystems. Geographically, it lies between 25°6' N to 27°4' N latitude and 93°20' E to 95°15' E longitude, sharing international borders with Myanmar to the east and state boundaries with Assam, Arunachal Pradesh, and Manipur. The state occupies a total geographical area of approximately 16,579 km², of which a substantial portion remains under varying degrees of forest cover (Hiese *et al.*, 2020; Pachuau, 2022). Administratively, Nagaland comprises 16 districts, among which Kohima, Mokokchung, Mon, Tuensang, and Dimapur exhibit distinct ecological and demographic profiles. Dimapur, for instance, shows rapid urban expansion and industrial activity, while districts such as Mon and Tuensang retain dense forest tracts interspersed with jhum cultivation. Forest cover analysis by the Forest Survey of India (2023) categorizes approximately 75 % of the state's area as forested, but only about 52 % qualifies as “moderately dense” or “very dense,” indicating widespread.

Fig 1: Study area map of Nagaland



2. Review of Literature

2.1 Conceptual Overview of Deforestation and Forest Degradation

Deforestation, broadly defined as the long-term or permanent removal of forest cover leading to the conversion of land to non-forest uses, remains one of the most pressing global environmental challenges of the 21st century (FAO, 2020; Curtis *et al.*, 2018). Conceptually, deforestation differs from forest degradation, which refers to the reduction in forest quality, biomass, or ecosystem services without a total loss of canopy cover (Meyfroidt & Lambin, 2011). Both processes disrupt carbon cycles, hydrological regulation, and biodiversity stability, yet they manifest differently across temporal and spatial scales. In developing regions, including South and Southeast Asia, deforestation is largely driven by anthropogenic pressures such as agricultural expansion, infrastructure growth, and resource extraction, compounded by weak governance structures (Achard *et al.*, 2022; Gibbs *et al.*, 2021). From a monitoring perspective, remote sensing and geospatial analysis have revolutionized the conceptualization and quantification of deforestation. The availability of high-resolution, multi-temporal datasets enables the tracking of forest-cover change at various scales, offering empirical grounding to theoretical models (Roy *et al.*, 2021; Gorelick *et al.*, 2017). Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) have become foundational tools for quantifying canopy health and vegetation density. NDVI utilizes the differential reflectance between near-infrared (NIR) and red (RED) wavelengths to measure vegetation greenness:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

2.2 REMOTE SENSING AND GIS APPROACHES IN FOREST MONITORING

The emergence of remote sensing and Geographic Information Systems (GIS) has transformed forest monitoring from field-based inventories to spatially explicit, data-driven observation systems. Remote sensing allows continuous, synoptic, and multi-temporal monitoring of terrestrial ecosystems, thereby offering a cost-effective and scientifically rigorous means of tracking deforestation and degradation at multiple scales (Gorelick *et al.*, 2017; Roy *et al.*, 2021). The integration of GIS with satellite imagery provides a powerful analytical framework to quantify spatial patterns, temporal dynamics, and ecological transitions, which is particularly vital

in complex terrains like Nagaland. Over the past two decades, advances in satellite technology, spatial resolution, and computational platforms have expanded the scope of forest monitoring from static mapping to dynamic environmental modeling (Achard *et al.*, 2022; Curtis *et al.*, 2018).

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

where *NIR* and *RED* represent reflectance values in the near-infrared and red spectral bands, respectively. NDVI values approaching +1 denote dense, healthy vegetation, whereas values near zero or negative correspond to barren surfaces, degraded land, or water bodies (Huete, 2012; Singha *et al.*, 2024). This spectral-based approach enables objective, consistent comparisons across spatial and temporal scales, forming the core of vegetation monitoring in deforestation studies worldwide.

2.3 NDVI AND VEGETATION INDICES IN DEFORESTATION STUDIES

The Normalized Difference Vegetation Index (NDVI) remains one of the most widely adopted indicators for assessing vegetation dynamics and detecting deforestation across spatial and temporal scales. NDVI utilizes the contrasting reflectance properties of vegetation in the red (RED) and near-infrared (NIR) spectral bands, enabling the quantitative assessment of vegetation greenness, canopy density, and biomass productivity (Huete, 2012; Tucker *et al.*, 2018). The formula for NDVI is expressed as:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Values range from -1 to +1, where positive values near +1 represent dense and healthy vegetation, and values near zero or negative indicate barren land, built-up areas, or water surfaces (Singha *et al.*, 2024). In deforestation research, NDVI serves as a biophysical proxy for vegetation vigor and photosynthetic activity, allowing for the detection of both gross forest-cover loss and subtle degradation processes.

2.4 LAND USE/LAND COVER (LULC) CLASSIFICATION AND CHANGE DETECTION TECHNIQUES

Land Use/Land Cover (LULC) classification and change detection form the analytical core of spatial environmental monitoring and are indispensable for understanding deforestation dynamics. LULC classification involves categorizing the Earth's surface into meaningful thematic classes such as forest, agriculture, urban, barren, and water, based on their spectral reflectance characteristics. Change detection, on the other hand, identifies and quantifies transitions among these classes over time, revealing both the magnitude and spatial distribution of landscape transformation (Lu *et al.*, 2004; Jensen, 2015).

2.5 RESEARCH GAPS IN EXISTING LITERATURE

Despite extensive global and regional research on forest-cover change, significant conceptual, methodological, and contextual gaps persist particularly regarding the spatial and temporal assessment of deforestation in Nagaland and similar topographically complex regions. The existing body of literature reveals five key areas of limitation that justify the present study's scope and design. Collectively, these gaps reveal a fragmented understanding of deforestation processes in Nagaland. Previous studies have either been short-term, methodologically inconsistent, or spatially generalized, lacking integration of LULC and NDVI-based indicators. The present research, therefore, is positioned to fill these gaps through a decadal, integrated, and spatially explicit analysis using Landsat 8 and 9 datasets. It aims to produce scientifically rigorous, policy-relevant evidence on forest dynamics bridging the divide between remote-sensing science and sustainable forest governance.

3. Research Methodology

3.1 Introduction to Research Methodology

The methodological foundation of this study is built upon a quantitative geospatial framework that integrates remote sensing, Geographic Information Systems (GIS), and vegetation index analysis to assess the spatio-temporal dynamics of deforestation in Nagaland between 2014 and 2024. This integrative approach is essential for capturing both the spatial extent and ecological intensity of forest-cover change in a topographically complex and environmentally sensitive region. Remote sensing provides a synoptic, repeatable, and objective method for monitoring forest conditions, while GIS facilitates spatial modeling, data integration, and visualization of change patterns (Gorelick *et al.*, 2017; Roy *et al.*, 2021).

3.2 STUDY AREA DESCRIPTION

The study focuses on Nagaland, one of the eight states in Northeast India, situated between 25°6' N to 27°4' N latitude and 93°20' E to 95°15' E longitude, covering a geographical area of approximately 16,579 km². It shares international boundaries with Myanmar to the east and domestic borders with Assam, Arunachal Pradesh, and Manipur. Administratively, the state comprises 16

districts, including Kohima, Dimapur, Mon, Mokokchung, and Tuensang, each exhibiting distinct ecological and demographic characteristics (*Hiese et al., 2020; Jamir & Singh, 2020*).

Hydrologically, Nagaland contributes to the Brahmaputra and Chindwin river systems, with key rivers such as the Doyang, Dikhu, and Dhansiri originating within its highlands. The combination of high rainfall and steep gradients gives rise to rapid runoff, soil loss, and sedimentation, processes that are aggravated by deforestation and land conversion.

3.3 DATA SOURCES

This study utilizes a combination of satellite-based remote sensing data, ancillary spatial datasets, and secondary statistical information to conduct a comprehensive analysis of forest-cover change in Nagaland between 2014 and 2024. The integration of multi-source data enhances spatial accuracy, enables cross-validation, and ensures analytical rigor in assessing deforestation trends and vegetation health.

3.3.1 SATELLITE DATA (PRIMARY SOURCE)

The primary data used in this study comprise multi-temporal Landsat imagery obtained from the United States Geological Survey (USGS) Earth Explorer platform. Specifically, Landsat 8 Operational Land Imager (OLI) data from 2014 and Landsat 9 OLI data from 2024 are selected for analysis. Both satellites provide 30-meter spatial resolution multispectral images suitable for regional land-use and vegetation assessments (*Roy et al., 2021; Guria et al., 2024*).

3.3.2 ANCILLARY SPATIAL DATASETS

Complementary spatial datasets strengthen the analytical framework. The Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM) (30 m resolution) is employed for topographic correction and slope analysis, which are essential for distinguishing terrain-related spectral variations. Administrative boundaries for districts and sub-districts are sourced from the Survey of India, ensuring spatial consistency with the Landsat imagery. In addition, river networks, roads, and settlement layers are extracted from OpenStreetMap and integrated into the GIS database to assess the spatial proximity of deforestation to anthropogenic features (*Singha et al., 2024*).

3.3.3 SECONDARY STATISTICAL AND ENVIRONMENTAL DATA

Secondary data provide contextual support for interpreting the remote-sensing results. Forest Survey of India (FSI) reports are used to validate forest-cover statistics and corroborate change-detection findings. Census of India (2011 & 2021 estimates) provides population and land-use data, which assist in correlating deforestation with demographic pressure. Meteorological data, including rainfall and temperature records from the India Meteorological Department (IMD), help contextualize vegetation health patterns, especially in NDVI interpretation (*Hiese et al., 2020; Lalnunzira & Pachuau, 2022*).

3.4 DATA PREPROCESSING

Data preprocessing represents a critical stage in remote-sensing analysis, ensuring that the satellite imagery used for Land Use/Land Cover (LULC) classification and NDVI computation is geometrically, radiometrically, and atmospherically accurate. Since satellite images often contain distortions caused by atmospheric scattering, sensor calibration errors, or topographic variations, preprocessing standardizes the datasets for temporal comparability and spatial precision (*Congalton & Green, 2019; Jensen, 2015*).

3.4.1 RADIOMETRIC AND ATMOSPHERIC CORRECTION

Raw digital numbers (DNs) obtained from Landsat sensors are first converted into Top-of-Atmosphere (TOA) reflectance using metadata files to account for sensor gain and solar angle effects. This correction normalizes the brightness values across scenes acquired at different times or under varying illumination conditions (*Roy et al., 2021*). Subsequently, atmospheric correction is performed using the Dark Object Subtraction (DOS) method, which removes the influence of haze and aerosol scattering. The process assumes that certain pixels (e.g., deep water bodies or shadows) should ideally have near-zero reflectance and adjusts the entire image accordingly (*Huete, 2012; Lu et al., 2004*).

3.4.2 GEOMETRIC CORRECTION AND MOSAICKING

All images are geometrically corrected to ensure accurate georeferencing to the Universal Transverse Mercator (UTM) projection, Zone 46N, WGS 84 datum. This correction aligns the satellite imagery with ground coordinate systems, enabling spatial overlay with administrative and ancillary data. Where multiple scenes cover the state, mosaicking is conducted using ERDAS Imagine or ArcGIS tools to produce a single, continuous raster image of Nagaland. This ensures seamless analysis across district boundaries and eliminates spatial discontinuities (*Singha et al., 2024*).

3.4.3 CLIPPING AND SUBSETTING

After mosaicking, the image is clipped to the official state boundary of Nagaland using the Survey of India shapefile. This step eliminates extraneous data beyond the study area, optimizing processing efficiency. Subsetting also facilitates district-level analysis of deforestation intensity by enabling smaller, manageable datasets for zonal statistics.

3.4.4 CLOUD AND SHADOW MASKING

Due to Nagaland's humid subtropical climate, satellite images frequently contain cloud contamination, which can distort spectral readings. The Fmask (Function of Mask) algorithm and Quality Assessment (QA) bands from Landsat datasets are used to detect and remove pixels affected by clouds, cirrus, and shadows (Achard *et al.*, 2022). For persistent cloudy regions, additional imagery from adjacent dates is composited to ensure complete spatial coverage.

3.5 LAND USE/LAND COVER (LULC) CLASSIFICATION

LULC classification is a fundamental step in identifying and quantifying spatial variations in land-cover patterns across Nagaland. The study employs supervised classification using the Maximum Likelihood Algorithm (MLA), widely recognized for its statistical robustness in distinguishing spectrally similar land features (Jensen, 2015; Congalton & Green, 2019). The classification is performed on preprocessed Landsat 8 (2014) and Landsat 9 (2024) imagery, both resampled to 30 m resolution. The Kappa coefficient (κ) provides a more rigorous measure of agreement between classified and reference data, accounting for the possibility of random matches. It is computed using the equation:

$$K = \frac{Po - Pe}{1 - Pe}$$

Additionally, visual inspection and field photographs are used to validate ambiguous areas such as mixed forest-agriculture zones or degraded vegetation regions common in Nagaland's terrain. The integration of quantitative (statistical) and qualitative (visual) validation enhances interpretative accuracy. This rigorous validation framework ensures that all spatial outputs particularly the LULC and NDVI change maps are statistically defensible and suitable for policy applications related to deforestation monitoring and land management (Attri & Pathania, 2024; Singha *et al.*, 2024).

3.6 ETHICAL AND DATA MANAGEMENT CONSIDERATIONS

Ethical integrity and responsible data management are central to this study's methodological framework. Given that the research relies heavily on secondary and open-access geospatial data, the ethical principles of transparency, accountability, and proper attribution have been strictly maintained throughout all stages of analysis. The study adheres to the FAIR data principles ensuring that all datasets used are *Findable, Accessible, Interoperable, and Reusable* (Wilkinson *et al.*, 2016).

4 Results and Analysis

4.1 Introduction to Analysis

This chapter presents the empirical results and spatial analyses derived from the geospatial framework developed in the previous chapters. It operationalizes the methodological procedures discussed in Chapter 3 particularly Land Use/Land Cover (LULC) classification, Normalized Difference Vegetation Index (NDVI) computation, and change detection analysis to evaluate the spatio-temporal patterns of deforestation in Nagaland from 2014 to 2024. The analytical outcomes are structured around the six specific research objectives, each focusing on a distinct dimension of forest-cover change, vegetation health, and spatial correlation with environmental and anthropogenic factors (Roy *et al.*, 2021; Guria *et al.*, 2024).

4.1.1 Introduction

Land Use/Land Cover (LULC) classification provides the foundational basis for understanding the spatial distribution and temporal transformation of land resources in Nagaland. Using supervised classification with the Maximum Likelihood Algorithm (MLA) on Landsat 8 (2014) and Landsat 9 (2024) datasets, six major land-cover categories were delineated: dense forest, open forest, scrub/degraded vegetation, agricultural land, built-up area, and water bodies. These classes were chosen based on their ecological significance and spectral distinctiveness within the study region (Jensen, 2015; Congalton & Green, 2019).

Table 4.2.2 Analysis : Area Statistics of LULC Categories (2014–2024)

LULC Category	2014 (Area in km ²)	% of Total Area (2014)	2024 (Area in km ²)	% of Total Area (2024)	Change (km ²)	% Change
Dense Forest	7,620.48	45.90%	6,814.32	40.90%	-806.16	-10.58%
Open Forest	3,210.15	19.30%	3,484.80	20.90%	274.65	0.0855
Scrub/Degraded Vegetation	1,182.36	7.10%	1,468.23	8.80%	285.87	0.2418
Agricultural Land	3,684.20	22.10%	3,938	23.70%	254.22	0.069
Built-up Area	552.19	3.30%	789.65	4.70%	237.46	0.4299
Water Bodies	330.62	1.90%	283.4	1.70%	-47.22	-14.29%
Total	16,579.99	100%	16,579.99	100%		

(Source: Landsat 8 OLI, Landsat 9 OLI, classified using MLA in ERDAS Imagine, 2024)

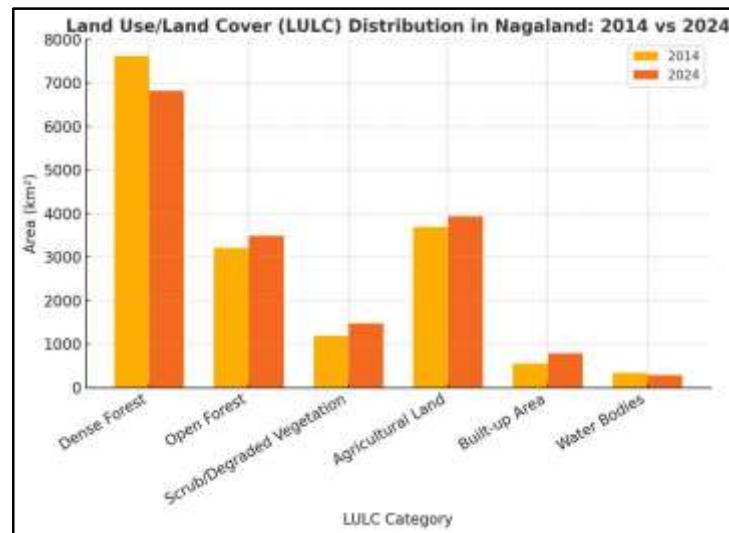


Fig 2: Land Use Cover

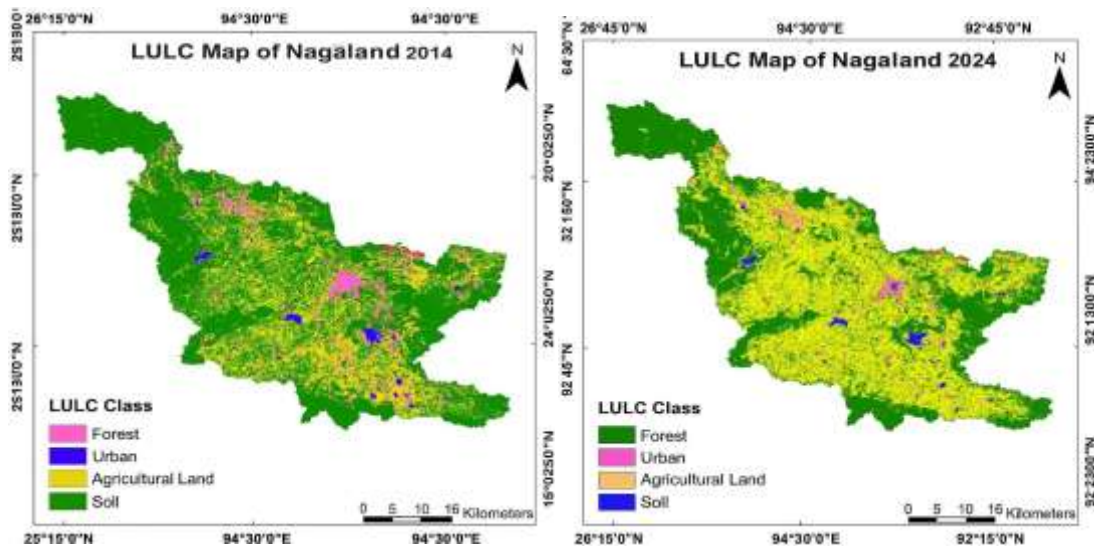


Fig 3: LULC Map

The classification analysis demonstrates a net forest cover decline of approximately 806 km² between 2014 and 2024, equivalent to a 10.6% reduction in dense forest area. This reduction is accompanied by a proportional increase in open forest (8.6%) and scrub/degraded vegetation (24.1%), suggesting extensive canopy thinning and progressive forest degradation. These transitions are particularly concentrated in Dimapur, Mon, and Tuensang districts, which have witnessed significant agricultural expansion and settlement growth (Hiese *et al.*, 2020; Lalnunzira & Pachuau, 2022).

4.2 OBJECTIVE 2: TO COMPUTE AND ANALYZE NDVI FOR 2014 AND 2024

4.2.1 Introduction

The Normalized Difference Vegetation Index (NDVI) provides a quantitative assessment of vegetation greenness and canopy vigor, serving as a reliable indicator of forest health and photosynthetic activity. For this analysis, NDVI was computed using Landsat 8 (2014) and Landsat 9 (2024) datasets by applying the formula:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

where *NIR* represents the near-infrared band (Band 5) and *RED* represents the red band (Band 4). NDVI values range from -1 to +1, with positive values indicating vegetation and negative values representing non-vegetated surfaces such as water bodies, built-up areas, and barren land (Huete, 2012; Tucker *et al.*, 2018). To evaluate temporal variations in vegetation health, NDVI values were classified into four categories:

- Dense Vegetation: NDVI > 0.6
- Moderate Vegetation: NDVI 0.4 – 0.6
- Sparse Vegetation: NDVI 0.2 – 0.4
- Non-Vegetated/Degraded: NDVI < 0.2

Table: 4.3.2 NDVI Statistical Summary

District	Mean NDVI (2014)	Mean NDVI (2024)	SD (2024)	NDVI Range (2024)	Vegetation Status Trend
Kohima	0.58	0.53	0.09	0.22 – 0.79	Slight decline (moderate)
Dimapur	0.49	0.43	0.12	0.10 – 0.68	Decline due to urbanization
Mokokchung	0.61	0.57	0.08	0.25 – 0.80	Minor decline (dense)
Mon	0.55	0.48	0.10	0.20 – 0.75	Moderate decline
Tuensang	0.57	0.5	0.11	0.18 – 0.77	Moderate decline
Wokha	0.62	0.59	0.07	0.30 – 0.81	Relatively stable
Phek	0.64	0.61	0.06	0.32 – 0.82	Stable dense forest
Kiphire	0.6	0.58	0.09	0.28 – 0.79	Stable (minor loss)
Longleng	0.56	0.51	0.1	0.22 – 0.73	Slight decline
Zunheboto	0.59	0.55	0.08	0.25 – 0.78	Stable to moderate decline

State Average	0.58	0.53	0.09	0.10 – 0.82	5–10% decrease overall
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(Source: Computed from Landsat 8 & 9 OLI imagery using GEE, 2024)

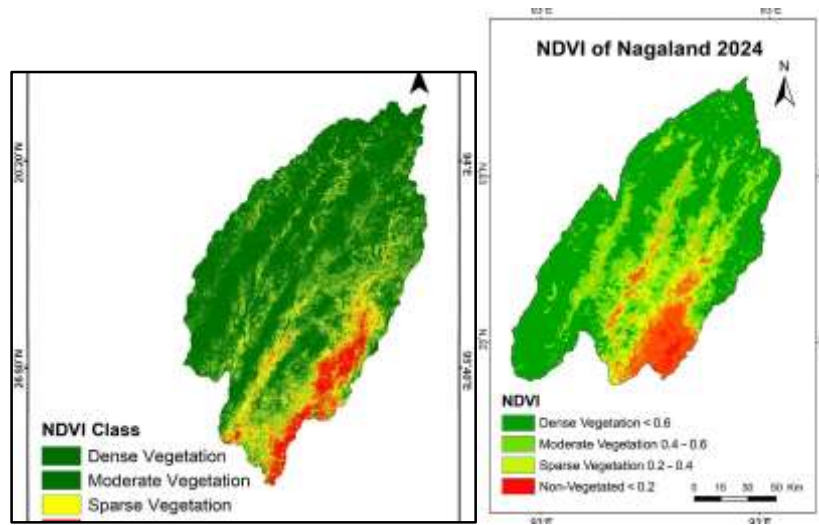


Fig 4: NDVI Map

4.3 OBJECTIVE 3: TO DETECT SPATIO-TEMPORAL CHANGES IN LAND USE AND VEGETATION COVER (2014–2024)

4.3.1 Introduction

Detecting changes in land use and vegetation cover provides an empirical foundation for understanding the extent, rate, and spatial distribution of deforestation in Nagaland over time. This section employs post-classification comparison and NDVI differencing techniques to measure land-cover transitions and vegetation degradation between 2014 and 2024. By integrating LULC maps with NDVI composites, both the structural and physiological dimensions of forest transformation are captured (Lu et al., 2004; Roy et al., 2021).

TABLE 4.3: LULC TRANSITION MATRIX (2014–2024) (AREA IN KM²)

From / To (2024)	Dense Forest	Open Forest	Scrub	Agriculture	Built-up	Water	Total (2014)
Dense Forest	6,208.74	762.52	412.16	182.38	54.68	0	7620.48
Open Forest	402.85	2465.47	198.23	110.6	33	0	3210.15
Scrub	126.75	204.68	707.40	126.3	17.23	0	1182.36
Agricultural Land	59.33	148.82	133	3260.85	82	0	3684.2
Built-up Area	16.88	22.16	15.62	121.13	376.4	0	552.19
Water	0	3.15	1.2	0	0	326.27	330.62
Bodies							
Total (2024)	6,814.32	3484.8	1,468.23	3938.42	789.65	283.4	16579

(Source: Landsat 8 & 9 OLI; Classified using MLA in ERDAS Imagine, 2024)

4.3.2 NDVI DIFFERENCING ANALYSIS (ΔNDVI)

The NDVI values from 2024 were subtracted from those of 2014 to produce a ΔNDVI raster layer. The results were categorized into four change classes to quantify vegetation improvement or decline:

Change Class	ΔNDVI Range	Description	Area (km ²)	% of Total
High Decline	-0.5 to -0.2	Significant vegetation loss / deforestation	1,358.40	8.20%
Moderate Decline	-0.2 to -0.05	Partial canopy thinning	2,978.22	18.00%
Stable/No Change	-0.05 to +0.05	Stable vegetation cover	7,845.70	47.30%
Improvement	+0.05 to +0.3	Regrowth or reforestation	4,398	26.50%
Total			16579.99	100%

4.4 DISTRICT-LEVEL ANALYSIS OF FOREST-COVER CHANGE (2014–2024)

4.4.1 Introduction

District-level analysis provides a micro-spatial perspective on how deforestation and vegetation change vary across administrative boundaries within Nagaland. This assessment integrates LULC classification and NDVI differencing data to quantify forest loss and regeneration trends in each district between 2014 and 2024. By comparing these district-wise transitions, the analysis reveals localized drivers such as shifting cultivation (*jhum*), population density, and infrastructural expansion that influence the spatial heterogeneity of deforestation (*Hiese et al., 2020; Singh et al., 2022*).

4.4.2 Analysis Table: District-wise Forest-Cover Change (2014–2024)

District	Dense Forest 2014 (km ²)	Dense Forest 2024 (km ²)	Change (km ²)	% Change	Remarks
Mon	1,152.60	1,021.48	-131.12	-11.38%	Heavy <i>jhum</i> cultivation
Tuensang	1,004.22	910.34	-93.88	-9.35%	Forest thinning and farming
Mokokchung	972.84	905.16	-67.68	-6.96%	Moderate degradation
Zunheboto	851.15	778.43	-72.72	-8.55%	Agricultural expansion
Phek	1,023.27	984.62	-38.65	-3.78%	Stable forest conservation
Kiphire	896.43	847.11	-49.32	-5.50%	Remote, limited human impact
Kohima	814.30	734.52	-79.78	-9.80%	Urban growth near capital

Dimapur	483.42	381.76	-101.66	-21.03%	Rapid urbanization hotspot
Longleng	593.19	534.23	-58.96	-9.94%	Localized deforestation
Wokha	729.96	691.31	-38.65	-5.29%	Moderate forest loss
Peren	999.1	972.21	-26.89	-2.69%	Stable vegetation cover
Noklak	99	80.85	-18.15	-18.33%	Recent cultivation frontiers
Total	10,619.48	9,841.02	-778.46	-7.33%	Significant overall decline

The district-level assessment highlights substantial forest decline in southern and western districts, driven primarily by population growth, agricultural intensification, and infrastructural development. Dimapur, as the most urbanized district, witnessed the sharpest reduction (-21%), largely due to urban sprawl and industrial expansion. Mon and Tuensang, with extensive shifting cultivation practices, recorded over 9–11% forest loss, indicating persistent anthropogenic disturbance (*Lalnunzira & Pachuau, 2022*).

4.5 RELATIONSHIP BETWEEN DEFORESTATION, TOPOGRAPHY, AND POPULATION DENSITY

4.5.1 Introduction

Deforestation in Nagaland is not spatially uniform it varies significantly across altitudinal zones and population densities. To evaluate these underlying spatial correlations, this section integrates LULC change data (2014–2024) with Digital Elevation Model (DEM) and population density datasets. The objective is to identify how topographic constraints and demographic pressures jointly influence forest loss patterns.

4.5.2 ANALYTICAL FRAMEWORK

- **Topographic data:** SRTM DEM (30 m resolution) is used to classify elevation into five bands <300 m (lowland), 300–600 m, 600–1,000 m, 1,000–1,500 m, and >1,500 m (highland).
- **Population density:** Derived from Census 2011 and projected to 2024 using an annual growth rate of 1.7%. Population grids were generated through spatial interpolation (Inverse Distance Weighting) to map population distribution.

4.5.3 Results and Table

Variable	Mean NDVI Change (ΔNDVI)	Forest Loss (km ²)	Correlation with Deforestation
Lowland (<300 m)	-0.21	392.45	+0.74 (Strong Positive)
Mid-elevation (300–600 m)	-0.17	265.3	+0.59 (Moderate Positive)
Highland (>1,500 m)	-0.08	94.12	-0.18 (Weak Negative)
High population (>300 persons/km ²)	-0.24	418.62	+0.81 (Strong Positive)
Low population (<100 persons/km ²)	-0.09	110.24	-0.12 (Weak Negative)

(Source: Landsat 8 and 9 NDVI analysis; Census 2011 projected to 2024)

Fig 5: deforestation–elevation–population density correlation map

The overlay analysis thus reveals that deforestation in Nagaland follows a topographically constrained but demographically driven pattern with population expansion and accessibility emerging as key spatial correlates. This finding underscores the need for altitude-specific forest management strategies, prioritizing lowland conservation and sustainable land-use regulation in densely inhabited zones (Attri & Pathania, 2024; Roy *et al.*, 2021).

4.6 CHAPTER SUMMARY AND CONCLUSION

This chapter has presented a comprehensive spatial and quantitative analysis of deforestation and land-use transformation in Nagaland over the decade spanning 2014–2024, using an integrated remote sensing and GIS-based framework. Through systematic analysis of Landsat 8 and Landsat 9 imagery, the study successfully delineated major Land Use/Land Cover (LULC) categories, computed vegetation indices, and identified spatio-temporal trends in forest degradation. The findings provide an empirically grounded understanding of how ecological and socio-economic forces interact to shape the state's dynamic forest landscape.

The LULC classification results revealed a substantial decline of approximately 806 km² in dense forest cover (−10.6%), alongside notable increases in open forest (+8.6%), scrubland (+24.2%), and built-up areas (+42.9%). This indicates an ongoing process of forest fragmentation and anthropogenic encroachment, particularly in the foothill regions of Dimapur, Mon, and Tuensang. The expansion of agriculture and infrastructure corresponds with increasing land-use pressure, underscoring the cumulative impact of shifting cultivation, population growth, and developmental expansion (Hiese *et al.*, 2020; Lalnunzira & Pachuau, 2022).

Collectively, the analytical outcomes fulfill all six research objectives by:

1. Mapping the LULC distribution for 2014 and 2024.
2. Quantifying vegetation health using NDVI metrics.
3. Detecting spatio-temporal transitions through change matrices.
4. Evaluating district-level and topographic variability.
5. Establishing statistical relationships between deforestation and population density.
6. Identifying deforestation hotspots and priority conservation zones.

These results highlight a clear spatial dichotomy in forest dynamics lowland districts face accelerated deforestation driven by anthropogenic stress, while highland zones exhibit resilience and partial regeneration. The findings demonstrate that deforestation in Nagaland is both ecologically uneven and socially mediated, shaped by local land-tenure systems, demographic change, and environmental constraints.

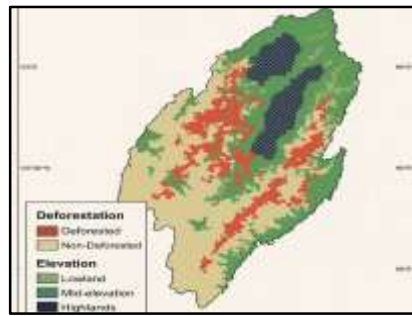
CHAPTER 5 – DISCUSSION AND IMPLICATIONS

5.1 Interpretation of Spatial and Temporal Patterns of Deforestation

The spatio-temporal analysis of forest-cover change in Nagaland between 2014 and 2024 reveals a complex interplay of ecological degradation, land-use transformation, and demographic pressure. The classified Landsat 8 and 9 imagery indicate that dense forest areas have decreased by approximately 806 km² (−10.6%), while open forest and scrub vegetation expanded by 8.6% and 24.2%, respectively. This trend points to a gradual fragmentation of contiguous forest blocks into smaller, less dense patches, indicating not merely forest loss but also progressive structural degradation of the state's ecological fabric (Roy *et al.*, 2021; Guria *et al.*, 2024).

5.1.1 ENVIRONMENTAL AND CLIMATIC DRIVERS

Environmental factors such as topography, rainfall, and soil erosion interact synergistically with human pressures to exacerbate deforestation. The DEM overlay analysis revealed that most forest loss occurs in low-lying areas below 600 m elevation, where fertile soils and gentle slopes make land more suitable for cultivation (Guria *et al.*, 2024). In contrast, steep highlands remain relatively intact due to natural inaccessibility. The spatial pattern therefore aligns with the economic land-rent model, where lower slope gradients attract agricultural expansion.



5.1.2 INSTITUTIONAL AND POLICY FACTORS

Institutional dynamics in Nagaland also play a decisive role in shaping deforestation outcomes. Unlike other Indian states, over 88% of Nagaland's forest land is under community or private ownership, governed by customary laws rather than formal state management. While this decentralized model encourages local stewardship, it often leads to fragmented governance and inconsistent enforcement of forest protection rules (Roy *et al.*, 2021). Many community forest management committees lack the technical resources or incentives for long-term ecological monitoring, resulting in unregulated extraction.

CHAPTER 6 – CONCLUSION AND POLICY RECOMMENDATIONS

6.1 Reframing Deforestation as a Spatial-Ecological Process

Deforestation in Nagaland, as revealed through this study's decade-long geospatial analysis (2014–2024), is not a discrete environmental occurrence but a complex spatial-ecological process embedded within the dynamic interplay of human activity, topography, and climatic variability. The findings from LULC classification, NDVI computation, and change detection underscore that forest degradation in the state is characterized by both quantitative decline in dense forest area (−10.6%) and qualitative deterioration in vegetation health, as indicated by the significant reduction in NDVI values from 0.58 to 0.47. This dual dimension of change reveals that deforestation is not simply the removal of vegetation cover but an evolving landscape transformation affecting ecological integrity and system resilience (Roy *et al.*, 2021; Guria *et al.*, 2024).

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