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Decadal analysis of forest canopy density changes in the southern Nagaland (2014 – 2024): A geospatial study of Dimapur, Kohima, and Peren districts

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Abstract

This study investigates forest cover changes in the southern districts of Nagaland including Dimapur, Kohima, and Peren, over a decade from 2014 to 2024. Using Forest Canopy density, the research integrates multiple vegetation indices such as the Advanced Vegetation Index (AVI), Bare Soil Index (BSI), Shadow Index (SI), Thermal Index (TI), Vegetation Density (VD), and Scale Shadow Index (SSI). The analysis reveals a significant decline in forest cover, and identifies areas of bare land, grassland, low forest, middle forest, and high forest. The findings highlight the need for community-led conservation strategies and the importance of implementing targeted measures to mitigate forest loss and ensure sustainable forest management in the region.

Keywords: *Forest cover change, Forest canopy density, multiple vegetation indices, Nagaland state*

Introduction

Forest resources are vital for sustaining ecosystems by regulating climate, preserving the soil, and providing food, medicinal herbs, and timber. However, forest resources are under immense pressure from anthropogenic activities such as deforestation, unsustainable land-use practices, resulting in declining forest cover and its resources. Therefore, understanding the spatial and temporal distribution of forest resources is crucial for ensuring sustainable forest management and conservation. According to the India State of Forest Report (ISFR) 2021, area under forest and tree cover has increased from 72.6 million hectares (21.92 % of India's geographical area) in 2019 to 80.9 million hectares (24.62 % of India's geographical area) in 2021, representing a net increase of 8.3 million hectares. While the forest cover for the country as a whole has shown a positive trend, in Nagaland state, according to the report (ISFR, 2021), shows a decrease in forest cover of 235 km^2 (1.88%) from 2019 to 2021. Thus, monitoring of forest cover change at the macro and micro levels is absolute necessity for policy intervention framework.

The application of geo-informatics, such as remote sensing and GIS, is used for the purpose of monitoring forest cover change and in identifying vulnerable areas, and is essential, especially in hilly and fragile mountainous ecosystems located in the

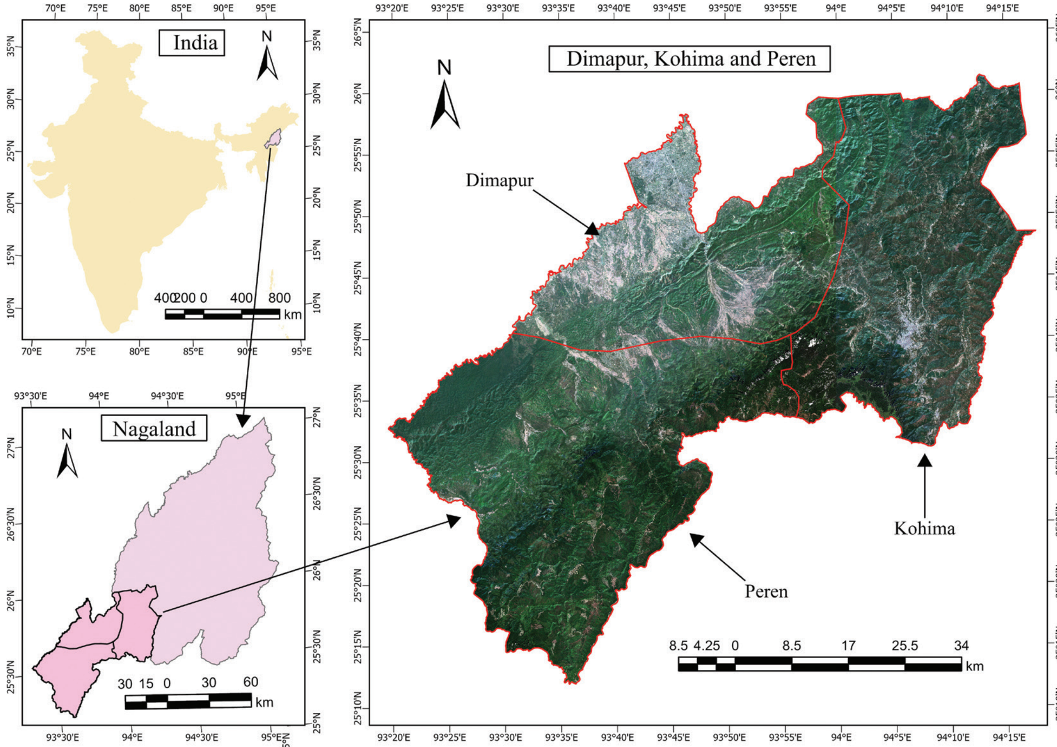

Fig. 1: Location of Dimapur, Kohima and Peren districts

Himalayan borderland. Different approaches are used for analyzing forest cover change, such as the object-based method (Gao *et al.*, 2016), the weights of evidence method (Silva *et al.*, 2017), deep neural network (Nguyen Thanh *et al.*, 2025; Khan *et al.*, 2017) maximum likelihood classifier (Giriraj *et al.*, 2008; Munsi *et al.*, 2012; Blaga *et al.*, 2023; Torahi *et al.*, 2011; Kundu *et al.*, 2020) NDVI technique (Nath, 2014; Tipula Yanapa *et al.*, 2024; Pasang *et al.*, 2022; Jadeja *et al.*, 2023). But when it comes to analyzing tree health through measurements of tree crown coverage, the Forest Canopy Density (FCD) is regarded as the most appropriate (Mshelia *et al.*, 2022; Abdollahnejad *et al.*, 2017). This model uses a multi-index approach that offers better differentiation between bare land and dense forests than traditional NDVI or land cover classification. Many researchers (Medhe & Badhe, 2024; Falensky *et al.*, 2020; Lu & Weng, 2007) agree that this model is the most efficient and cost-effective for quantifying the forest canopy. The FCD model calculates vegetation-related indices from medium-resolution multispectral satellite images and emphasizes the density of forest canopies. It represents the amount of foliage covering the ground when viewed from above. Therefore, analyzing changes in FCD provides valuable insights into the type and severity of forest cover change, and estimating changes.

Nagaland has rich biodiversity, unique ecosystems, and diverse land use patterns. The population is dependent on forests for livelihood and sustenance. Studies have been conducted (Sinha & Modak, 2023; Hiese *et*

Table 1: Acquisition of satellite data

Satellite	Sensor	Spatial resolution	Date	Source
LANDSAT 8	OLI/TIRS	30	27th Jan 2014	https://earthexplorer.usgs.gov/
LANDSAT 9	OLI-2/TIRS-2	30	15th Jan 2024	https://earthexplorer.usgs.gov/

al., 2020; Rawat *et al*., 2018; Pathan *et al*., 2024) on forest cover change in Nagaland and the cause-and-effect of forest loss, such as excessive logging, slash-and-burn farming (Jhum), and heavy use of firewood. This unsustainable practice is not only a challenge for forest management but may also jeopardize ecosystem health and human well-being, which requires proper investigation into the forest cover change. Several studies on forest cover changes in Nagaland have used geospatial techniques like supervised classification using a maximum likelihood classifier (Kiho, 2024; Ritse, 2020), a multi-criteria decision-making model (Guria *et al*., 2024), and NDVI analysis (Sinha & Modak, 2023; Pathan *et al*., 2024) for monitoring the forest cover change.

The present study focuses on analyzing the forest cover change in southern Nagaland, while considering the methodological gap, and aims to implement the forest canopy density model. The study considers the period between 2014 and 2024 to measure the forest cover change, limited to the districts of Dimapur, Kohima, and Peren.

Study area

The study area comprises the Kohima, Dimapur, and Peren districts of Southern Nagaland, located between 93°32'66.84" E and 94°29'87.71" E longitude, and 25°19'83.58" N to 26°02'17.67" N latitude (Fig. 1). Peren, known as the greenest district of the state, highlights areas of significant ecological importance and forest preservation. Kohima, the state capital, serves as a hub for administrative and socio-economic activities, offering an insight into the interplay between development and forest sustainability.

The districts provide a comprehensive framework to study forest cover density due to their distinct characteristics: Dimapur reflects the pressures of urbanization, Peren exemplifies ecological richness, and Kohima balances urban development with environmental management. By examining these varied landscapes, the study aims to uncover patterns of forest cover change.

Datasets and methodology

The satellite images for 2014 and 2024 are acquired from USGS Earth Explorer, including Landsat 8 for 2014 and Landsat 9 for 2024 (Table 1). Cloud cover was minimized by selecting cloud-free scenes, and atmospheric correction was performed by converting DN values to TOA radiance and reflectance using rescaling coefficients from the MTL file, followed by sun angle correction. To address seasonal variations, imagery from the same month (January) was used to maintain phenological consistency. These corrections improved the quality of reflectance values, ensuring reliable derivation of indices like AVI, BSI, and SI for FCD estimation.

Advanced Vegetation Index

The Advanced Vegetation Index (AVI) is a refined vegetation index developed to address the shortcomings of the Normalized Difference Vegetation Index (NDVI), especially in capturing subtle differences

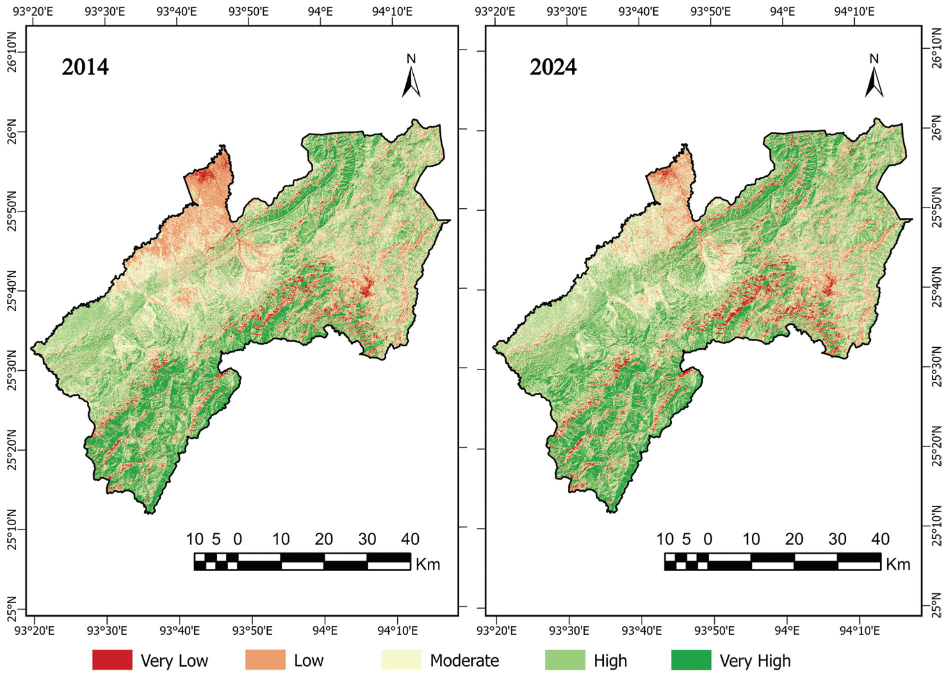

Fig. 2: Advanced vegetation index (AVI)

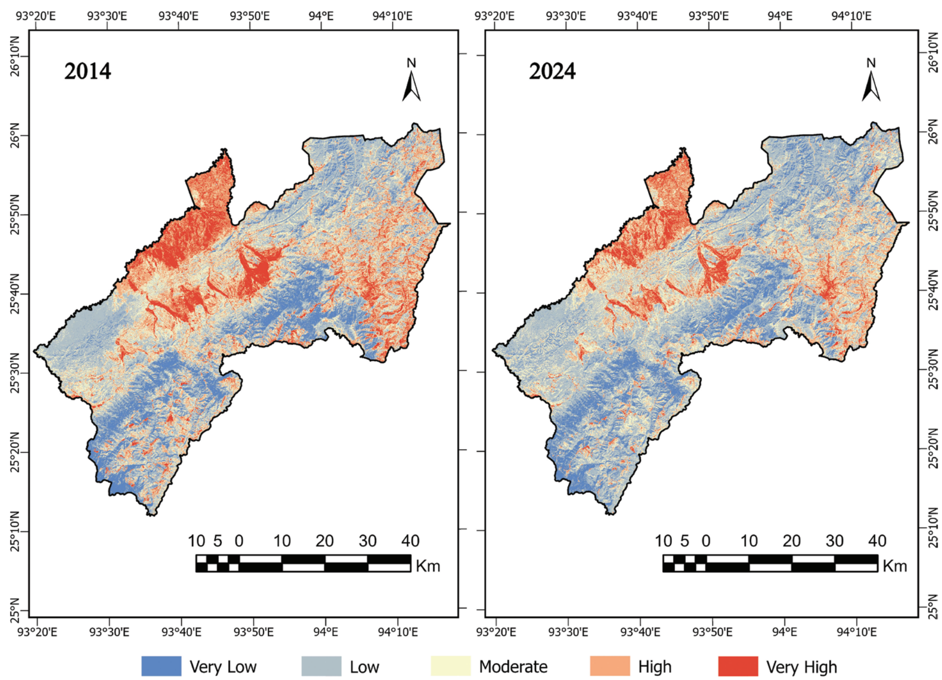

Fig. 3: Bare soil index

in forest canopy density. The utility of this index lies in its offering of greater sensitivity to variations in vegetation cover and structure by emphasizing the strength of the infrared signal. It also reduces the impact of atmospheric interference, providing more precise distinctions between dense and sparse canopy areas. This makes AVI especially valuable for analysing forests with diverse and complex vegetation patterns, where NDVI may not effectively reveal minor variations in canopy characteristics. The index is computed by using the following formula:

$$AVI = \{(NIR + 1)(65536 - RED)(NIR - RED)\}^{1/3}$$

Bare Soil Index

The Bare Soil Index (BSI) is a spectral reflectance-based index designed to evaluate land surface conditions, particularly in areas with limited vegetation cover. In such environments, conventional vegetation indices often yield less reliable results, necessitating complementary approaches like BSI. This index utilizes reflectance values from the short-wave infrared (SWIR), red, near-infrared (NIR), and blue bands to capture both soil and vegetation characteristics. BSI has proven helpful in distinguishing between agricultural and non-agricultural vegetation areas and in assessing forest canopy cover. By integrating soil exposure and vegetation information, BSI facilitates a more comprehensive understanding of land surface dynamics. The BSI is calculated by the following formula:

$$BSI = \frac{(SWIR + RED) - (NIR + BLUE)}{(SWIR + RED) + (NIR + BLUE)} \times 100 + 100$$

Shadow Index

The Shadow Index (SI) is a spectral metric employed to evaluate forest canopy structure by quantifying shadow patterns resulting from the spatial arrangement of trees. Derived from the low radiance values in visible spectral bands, SI exhibits higher values in mature, heterogeneous forest stands and lower values in younger, even-aged plantations. Furthermore, SI effectively differentiates between various land cover types, assigning minimal values to exposed soil, grasslands, and aquatic features, thereby proving useful in forest classification and canopy monitoring applications.

$$SI = \{(65536 - BLUE)(65536 - GREEN)(65536 - RED)\}^{1/3}$$

Thermal Index

The Thermal Index (TI) is a remote sensing-derived parameter that distinguishes forested from non-forested areas based on surface temperature variations. Forests exhibit lower temperatures due to canopy shading and evapotranspiration. TI utilizes thermal infrared band data to capture these cooling effects. Radiometric calibration and atmospheric correction are performed on the band to convert digital numbers (DN) to at-sensor radiance values. The thermal index is derived by combining TOA spectral radiance and the thermal constant value for the specified band as given below:

$$TI = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)}$$

L_λ - TOA spectral radiance (Watts/(m^2 sr^{-1} μm^{-1})

K_1 - Calibration Constant (Landsat 8- 774.8853, Landsat 9- 799.0284)

K_2 - Calibration Constant (Landsat 8- 1321.0789, Landsat 9-1329.2405)

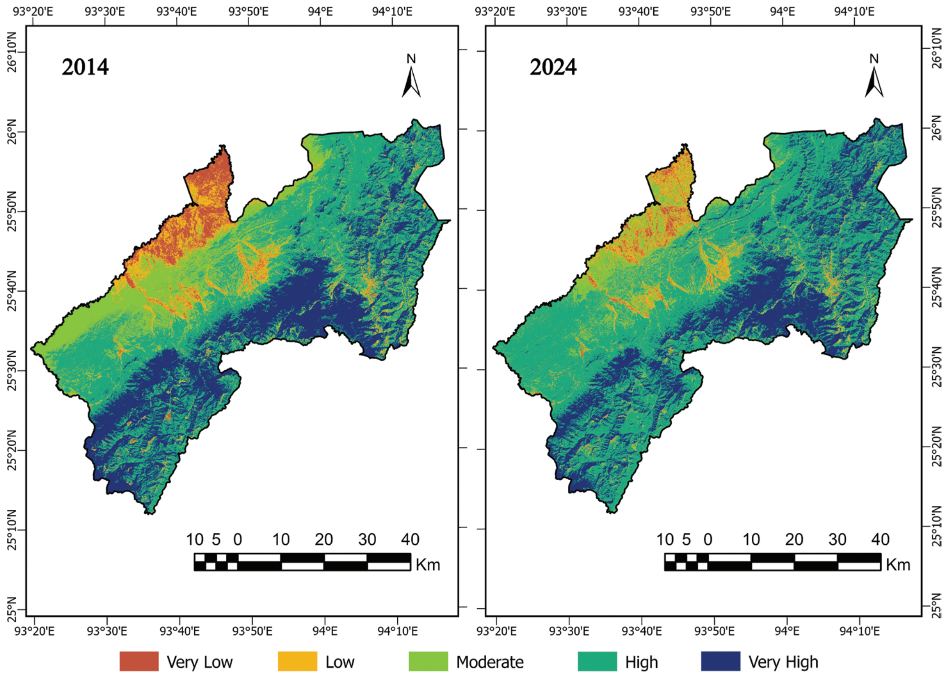

Fig. 4: Shadow index

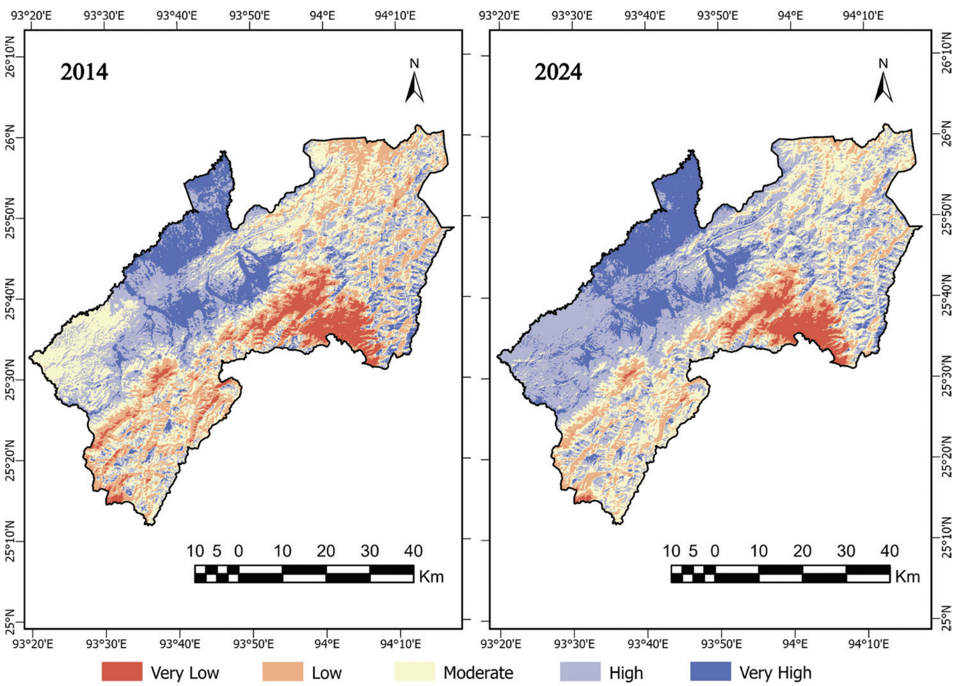

Fig. 5: Thermal index (TI)

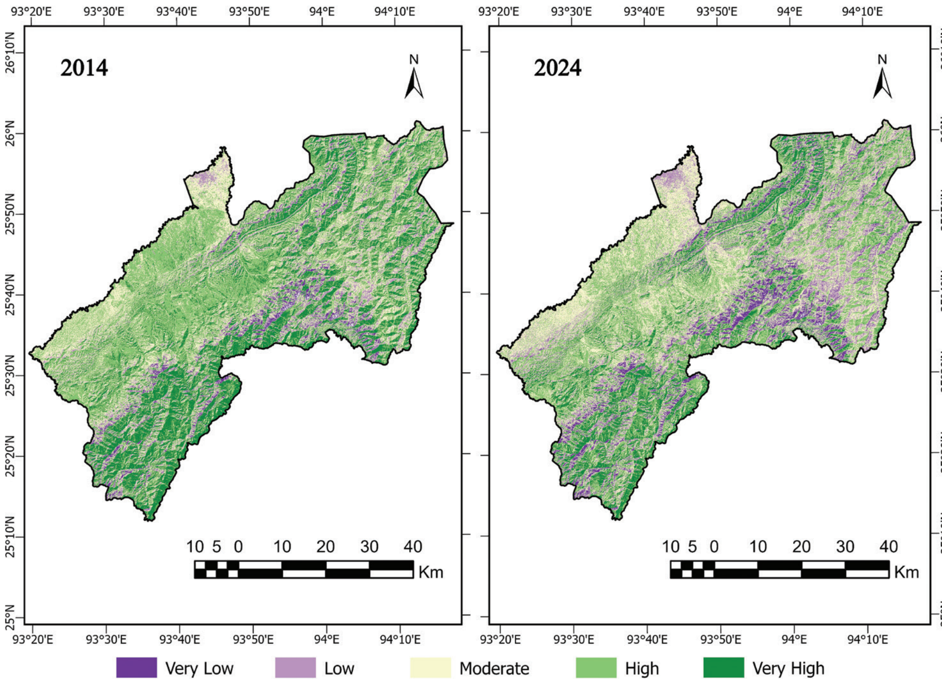

Fig. 6: Vegetation density

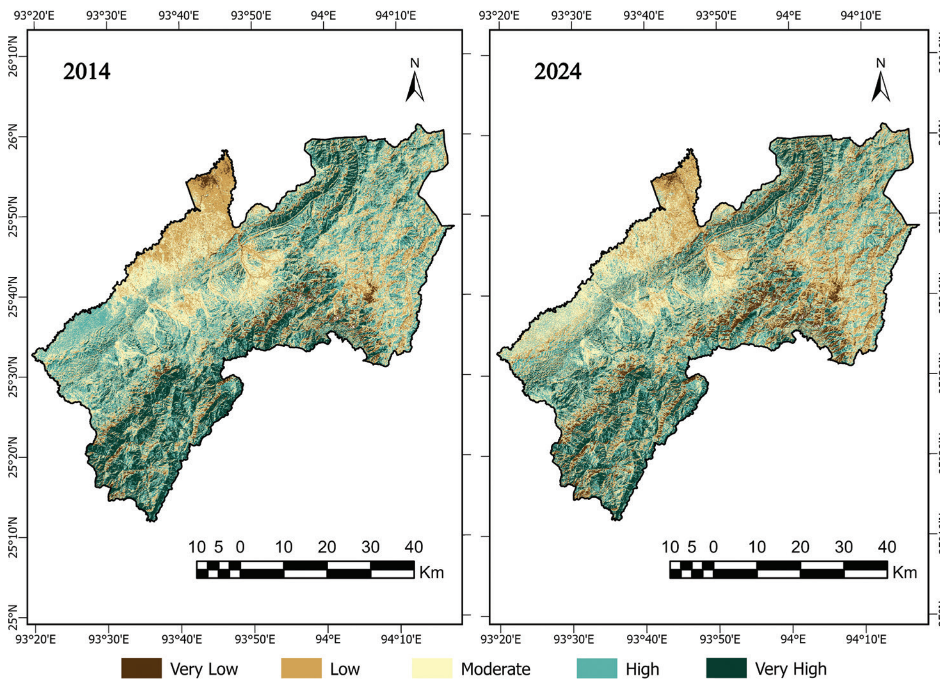

Fig. 7: Scale shadow index

Forest Canopy Density

Forest canopy density (FCD) is essential for examining forest cover conditions and monitoring forest transformations during forestry activities such as degradation or rehabilitation. It serves as a key indicator for evaluating forest condition, structural complexity, and canopy coverage. FCD is calculated using four biophysical factors: AVI, BSI, SI, and TI. The VD index is derived using the Advanced Vegetation Index (AVI) and the Bare Soil Index (BSI). The Scale Shadow Index (SSI) was developed to integrate Vegetation Index (VI) values and Shadow Index (SI) values specifically for forested areas. By integrating VD and SSI, the FCD values are effectively transformed, providing a comprehensive measure of forest canopy density. This model improves the differentiation between the upper canopy and ground vegetation. FCD values range from 0% (no canopy) to 100% (very dense canopy) and are calculated using the following formula:

$$FCD = \sqrt{VD \times SSI + 1} - 1$$

Result and discussion

Biophysical parameters

The AVI maps for 2014 and 2024 (Fig. 2) illustrate the spatial distribution and temporal change in vegetation density across the study area. In 2014, a significant part of the region exhibited low to moderate AVI values (light red to yellow shades), indicating sparse or moderately dense vegetation, especially in the northern and central parts. However, by 2024, there is a noticeable increase in high and very high AVI values (light to dark green), reflecting an improvement in vegetation health and canopy density across the central and south-western region. This positive shift suggests vegetation regeneration, afforestation efforts, or natural recovery in the landscape.

The BSI maps for 2014 and 2024 (Fig. 3) depict the distribution and intensity of bare soil areas across the study region. In 2014, extensive zones, particularly in the central and northern parts, show high to very high BSI values (orange to red shades), indicating widespread exposed soil. By 2024, there is a notable decline in very high BSI areas, replaced increasingly by low to moderate values (blue to yellow shades), particularly in northeastern regions, suggesting vegetation regrowth.

Figure 4 illustrates the Shadow Index (SI) distribution for 2014 and 2024. In 2014, northern and western areas show predominantly low SI values (brown-yellow), reflecting sparse canopy cover. By 2024, a notable increase in high SI values (green to blue) is observed, especially in central and eastern regions, indicating improved canopy density, while some degradation is evident in the northwest, highlighting spatial variations in forest health over time.

Figure 5 shows the thermal index for 2014 and 2024. In 2014, the southern and eastern areas exhibit very high thermal values, indicating warmer surfaces due to sparse vegetation and high built-up in the Kohima city. In contrast, northern and central regions show high to very high thermal zones in 2024, while a noticeable expansion of low to moderate zones (blue to yellow) reflects a rise in thermal index values, indicating improved vegetation.

Vegetation density (VD)

Figure 6 represents the vegetation density index for 2014 and 2024. In 2014, large part of the area exhibits high to very high vegetation density (light to dark green), indicating healthy forest cover. However, some low and very low-density patches (light and dark purple) are present, especially in central and northeastern zones. By 2024, there is a slight increase in low-density vegetation, suggesting degradation, particularly in the southern part. Despite this, the majority of the region still retains moderate to high vegetation density, indicating relatively stable forest health.

Scale Shadow Index (SSI)

Figure 7 displays the Scale Shadow Index (SSI) for 2014 and 2024, which reflects canopy shadow intensity after standardization. In 2014, the southern and southeastern regions show high to very high SSI values (blue-green), indicating denser canopy and better vegetation cover. Northern and western areas show low to moderate values (brown to yellow), suggesting sparser vegetation. In 2024, an overall increase in SSI values is observed across most areas, indicating improved canopy density, although some localized declines are noticeable.

Forest Canopy Density (FCD)

Figure 8 illustrates the Forest Canopy Density (FCD) of Dimapur for 2014 and 2024, highlighting regional changes. Between 2014 and 2024, the northern and central regions show a notable increase in bare land (23.03%). Grassland also expanded by 11.67%, due to the conversion of sparsely forested areas. The most notable decline was in low forest density, which decreased 21.05%, indicating substantial deforestation and degradation. The middle forest areas showed an increase of 15.62%, while high forest density exhibited the most promising growth, with an increase of 37.84% (Table 2), suggesting recovery in eastern and southeastern parts. The observed increase in forest cover in Dimapur is attributed to the implementation of multiple conservation initiatives. The Nagaland Forest Management Project (NFMP) under Japan International Cooperation Agency (JICA) rehabilitated 22,500 ha across 185 villages statewide (including Dimapur) (NFMP, 2024). Joint Forest Management (JFM) and National Afforestation Programme (NAP) enhanced community involvement. Agroforestry promotion comprises the integration of trees with jhum cultivation (Nagaland Forest Department, 2019). Forest plantations increased green cover, while awareness programs educated over 50,000 students and villagers (Nagaland Forest Department, 2023). These trends indicate a mixed scenario for Dimapur, with notable deforestation in low forest areas counterbalanced by gains in high and middle forest densities.

Kohima presents the most alarming trends among the three districts (Fig. 9). Bare land increased dramatically by 117.69%. Grassland saw a minor increase of 0.61%, suggesting limited expansion. The district experienced a decline in all categories of forest; low forest areas decreased by 4.49%, middle forest by 2.21%, and high forest density areas by 23.74%, as illustrated in table 2. The data highlight the significant challenges Kohima faces in sustaining forest density on the wake of extensive deforestation.

Peren shows a mixed but relatively stable trend compared to the other two districts (Fig. 10). Bare land increased by 62.45%, indicating notable land-use changes in the southern and central parts. Grassland, however, decreased

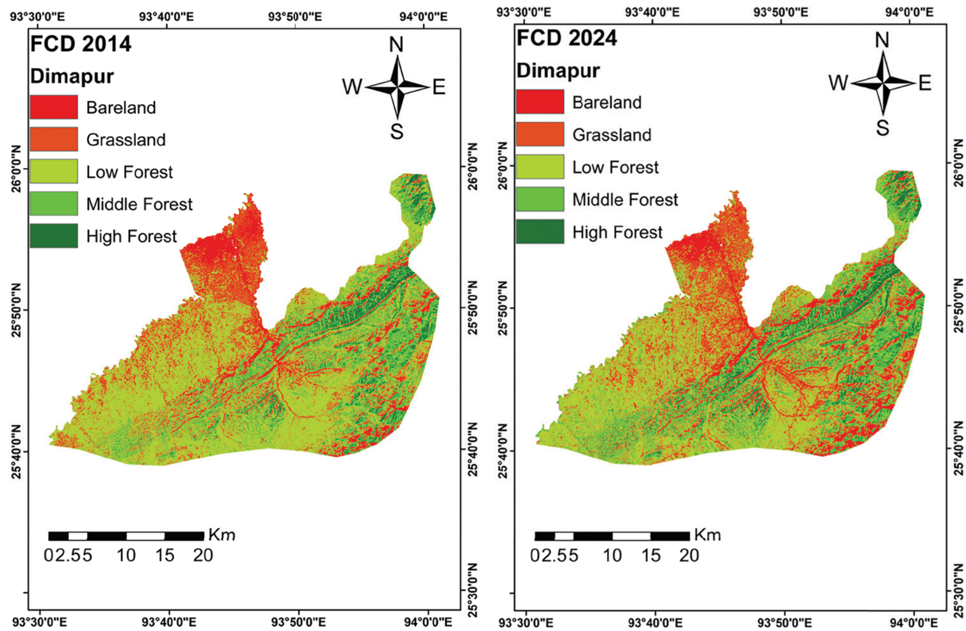

Fig. 8: Forest canopy density map of Dimapur for 2014 & 2024

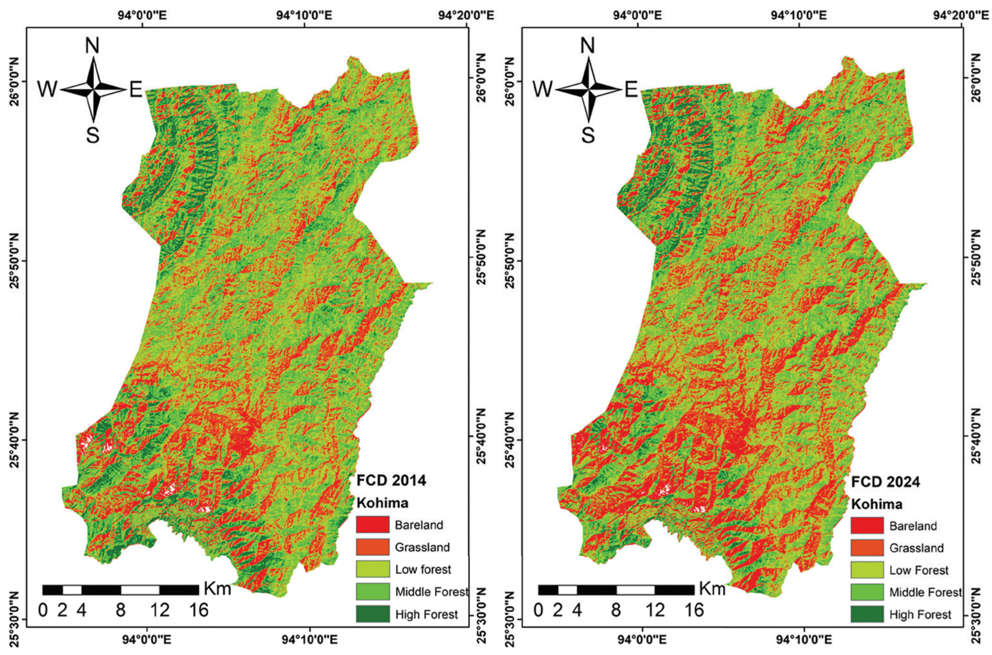

Fig. 9: Forest canopy density of Kohima for 2014 & 2024

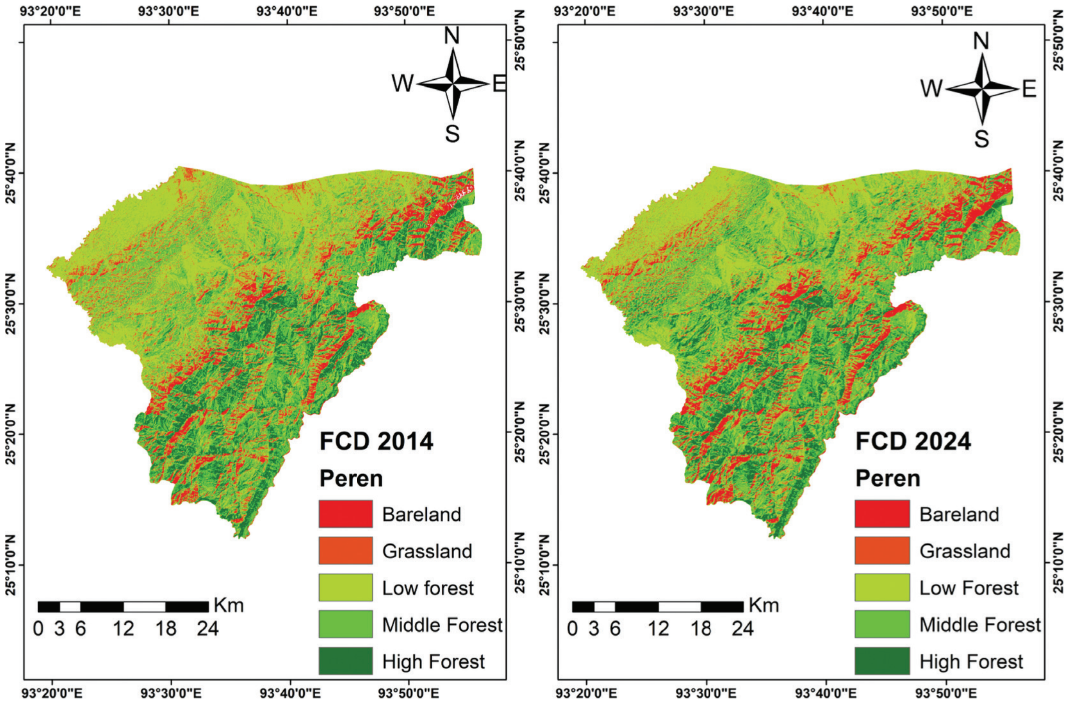

Fig. 10: Forest canopy density of Peren, 2014 & 2024

Table 2: Forest canopy density of Dimapur, Kohima, and Peren, 2014 - 2024

FCD Class	Dimapur			Kohima			Peren		
	Area (Km²)		Change (%)	Area (Km²)		Change (%)	Area (Km²)		Change (%)
	2014	2024	2014-2024	2014	2024	2014-2024	2014	2024	2014-2024
Bareland	80.22	98.69	23.02	75.45	164.24	117.68	77.85	126.48	62.46
Grassland	252.54	282	11.67	322.03	324.01	0.61	263.55	231.09	-12.31
Low Forest	446.2	352.26	-21.05	414.52	395.91	-4.48	619.04	574.3	-7.22
Middle Forest	157.14	181.68	15.61	353.69	310.53	-12.20	448.24	450.25	0.44
High Forest	56.31	77.62	37.84	118.37	90.27	-23.73	247.61	275.51	11.26

by 12.31%, due to shifts from grassland to other land uses. Low forest areas declined by 7.23%, reflecting ongoing deforestation. Middle forest areas remained relatively stable, with a slight increase of 0.45%, while high forest density exhibited positive growth, increasing by 11.27%. This growth in high forest density indicates effective forest management and forest regeneration efforts in the northern and eastern parts of the district (NFMP, 2021) despite the overall decline in low forest areas.

Table 3: Confusion matrix for the year 2014

	Bare land	Grassland	Low forest	Middle forest	High forest	Total	User's accuracy
Bare land	9	0	0	1	0	10	0.9
Grassland	0	25	3	0	0	28	0.89
Low Forest	0	4	28	2	1	35	0.8
Middle Forest	0	2	1	15	0	18	0.83
High Forest	0	0	0	1	9	10	0.9
Total	9	31	32	19	10	101	0
Producer's Accuracy	1	0.81	0.88	0.79	0.9	0	0.85
Overall Accuracy	85%						
Kappa Coefficient	0.8						

Table 4: Confusion Matrix for the year 2024

	Bare land	Grassland	Low forest	Middle forest	High forest	Total	User's accuracy
Bare land	6	1	3	0	0	10	0.6
Grassland	0	21	4	1	0	26	0.81
Low Forest	0	7	36	1	0	44	0.82
Middle Forest	0	0	0	16	0	16	1
High Forest	0	1	0	0	9	10	0.9
Total	6	30	43	18	9	106	0
Producer's Accuracy	1	0.7	0.84	0.89	1	0	0.83
Overall Accuracy	83%						
Kappa Coefficient	0.76						

The expansion of bare land in all three districts is alarming, particularly in Kohima, where it surged by 117.69%, while Dimapur and Peren exhibit encouraging improvements in dense forest cover, a result of effective conservation measures such as sustainable forestry practices and community awareness campaigns. However, the reduction in low and medium-density forests signals a pressing need for focused reforestation and protection efforts. Especially, Kohima demands immediate action to combat extensive deforestation and shifting land use.

Accuracy assessment

To evaluate the accuracy of the FCD classifications, an error matrix was generated by comparing the classified FCD maps with high-resolution reference data from Google Earth Pro. A stratified random sampling approach was employed, selecting 100 random pixels for each year to ensure representative validation.

The accuracy assessment revealed an overall accuracy of 85% and a kappa coefficient (k) of 0.80 for the 2014 FCD classification, indicating strong agreement with reference data. In contrast, the 2024 FCD classification exhibited an overall accuracy of 83% and a kappa coefficient of 0.76. The corresponding confusion matrices for 2014 and 2024 are presented in table 3 and table 4 respectively.

Conclusion

The study reveals significant forest cover changes across southern Nagaland consisting of Dimapur, Kohima, and Peren districts from 2014 to 2024. The findings demonstrate that Dimapur shows forest recovery, particularly in the eastern and southeastern parts. Kohima, in contrast, reflects the most pressing challenges, where forest degradation continues at concerning rates, underscoring the intensity of human-driven pressures. Peren stands out as a comparatively stable region where regeneration efforts and management strategies appear to have borne meaningful impact. The contrasting trajectories emphasize the urgent need for area-specific strategies that integrate conservation with sustainable land-use practices. The findings also highlight the need for community-led conservation strategies and the importance of implementing targeted measures to mitigate forest loss and ensure sustainable forest management. By prioritizing adaptive forest governance, community empowerment, and evidence-based monitoring, Nagaland can balance ecological preservation with developmental needs, aligning with global climate resilience goals.

Competing interest

The corresponding author declares that they have no conflict of interest.

References

Abdollahnejad, A., Panagiotidis, D., & Surový, P. (2017). Forest Canopy Density Assessment Using Different Approaches—Review. *Journal of Forest Science, 63*(3), 107–116. https://Doi.Org/10.17221/110/2016-JFS

Blaga, L., Ilieș, D. C., Wendt, J. A., Rus, I., Zhu, K., & Dávid, L. D. (2023). Monitoring Forest Cover Dynamics Using Orthophotos and Satellite Imagery. *Remote Sensing, 15*(12). https://doi.org/10.3390/RS15123168

Forest Survey of India (2019). *India State of Forest Report 2019 (Vols. I–II).* Ministry of Environment, Forest and Climate Change, Government of India.

Forest Survey of India (2021). *India State of Forest Report 2021 (Vols. I–II).* Ministry of Environment, Forest and Climate Change, Government of India.

Gao, Y., Gonzalez, I., Gonzalez, R., Lopez-Sanchez, J. G., Skutsch, M., Paneque-Gálvez, J., & Mas, J. F. (2016, September). Forest cover change analysis by object based method using spot and rapideye images.

In *6th International Conference on Geographic Object-Based Image Analysis, GEOBIA 2016: Solutions & Synergies*. University of Twente, Faculty of Geo-Information Science and Earth Observation (ITC). https://doi.org/10.3990/2.377

Giriraj, A., Irfan-Ullah, M., Murthy, M. S. R., & Beierkuhnlein, C. (2008). Modelling Spatial and Temporal Forest Cover Change Patterns (1973-2020): A Case Study from South Western Ghats (India). *Sensors 2008, Vol. 8, Pages 6132–6153, 8*(10), 6132–6153. https://doi.org/10.3390/S8106132

Guria, R., Mishra, M., Baraj, B., Goswami, S., Santos, C. A. G., Da Silva, R. M., & Bhutia, K. D. O. (2024). Examining the drivers of forest cover change and deforestation susceptibility in Northeast India using multicriteria decision-making models. *Environmental Monitoring and Assessment, 196*(11), 1098. https://doi.org/10.1007/s10661-024-13172-2

Hiese, N., Hiese, Z., Katiry, D., Medo, T., & Hiese, M. (2020). Evaluation Of Spatio-Temporal Aspects of Land Use and Land Cover Changes in Nagaland, North-East, India. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLIII-B3-2020*, 1547–1553. https://doi.org/10.5194/isprs-archives-XLIII-B3-2020-1547-2020

Jadeja, F., Vachhrajani, K., & H. Kalubarme, M. (2023). Assessment of Spatio-Temporal Changes of Forest Cover using Remote Sensing techniques in Pavagadh Region, Gujarat State. *International Journal of Environment and Geoinformatics, 10*(4), 39–47. https://doi.org/10.30897/IJEGEO.1344777

Khan, S. H., He, X., Porikli, F., & Bennamoun, M. (2017). Forest Change Detection in Incomplete Satellite Images with Deep Neural Networks. *IEEE Transactions on Geoscience and Remote Sensing, 55*(9), 5407–5423. https://doi.org/10.1109/TGRS.2017.2707528

Kiho, K., Manjari K. G. A, & Haokip, P. (2024). Assessing Urbanization Dynamics Through Land Use/Land Cover Change Detection in Zunheboto Sadar, Nagaland, India. *Current World Environment, 19*(2), 928. DOI:http://dx.doi.org/10.12944/CWE.19.2.32

Kundu, K., Halder, P., & Mandal, J. K. (2020). Forest cover change analysis in sundarban delta using remote sensing data and GIS. *Studies in Computational Intelligence, 784*, 85–101. https://doi.org/10.1007/978-981-13-7334-3_7

Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing, 28*(5), 823–870. https://doi.org/10.1080/01431160600746456

Medhe, R. S. & Badhe, Y. P. (2024). Forest Canopy Density Monitoring by Using Geospatial Techniques: A Study of Gadchiroli District, Maharashtra, India. *Current World Environment, 18*(3), 1312–1324. https://doi.org/10.12944/CWE.18.3.31

Mshelia, Z. H., Bamgboye, A. I., Onilude, M. A., & Taiwo, O. J. (2022). Geospatial modelling of Forest Canopy Density and Landscape Assessment in Omo Biosphere Reserve, South-western Nigeria. *Journal of Tropical*

Forestry and Environment, 11(02). https://doi.org/10.31357/JTFE.V11I02.5596

Munsi, M., Areendran, G., & Joshi, P. K. (2012). Modeling spatio-temporal change patterns of forest cover: A case study from the Himalayan foothills (India). *Regional Environmental Change, 12*(3), 619–632. https://doi.org/10.1007/S10113-011-0272-3/FIGURES/5

Nath, B. (2014). Quantitative Assessment of Forest Cover Change of a Part of Bandarban Hill Tracts Using NDVI Techniques. *Journal of Geosciences and Geomatics, 2*(1), 21–27. https://doi.org/10.12691/jgg-2-1-4

NFMP (2021). *Manual for Forestry and Conservation Models.* https://nfmpjica.org/media/1737/manual-for-forestry-conservation-models.pdf

Nguyen Thanh, H., Ho Le, T., Nguyen Van, D., Hoa Thuy, Q., Nguyen Kim, A., Le Duc, H., Pham Van, D., Phan Trong, T., & Tran Van, P. (2025). Forest cover change mapping based on Deep Neural Network, GIS, and High-resolution Imagery. *Vietnam Journal of Earth Sciences*, 151–175. https://doi.org/10.15625/2615-9783/22192

Pasang, S., Norbu, R., Timsina, S., Wangchuk, T., & Kubíček, P. (2022). Normalized difference vegetation index analysis of forest cover change detection in Paro Dzongkhag, Bhutan. *Computers in Earth and Environmental Sciences: Artificial Intelligence and Advanced Technologies in Hazards and Risk Management*, 417–425. https://doi.org/10.1016/B978-0-323-89861-4.00045-2

Pathan, S. A., & Atomi, V. (2024). Assessment of land use/land cover change and NDVI analysis in Wokha District, Nagaland, India. *Human Ecology, 52*(3), 549-561. https://doi.org/10.1007/s10745-024-00512-6

Rawat, M. S., Zhimo, V. V., & Imchen, N. (2018). Deforestation in Nagaland, North-East India: Causes, Effects and Subsequent Environmental Degradation-A Preliminary Review.*Global Journal of Current Research* Vol. 6 No. 3. 2018. Pp. 61-70.

Ritse, V., Basumatary, H., Kulnu, A. S., Dutta, G., Phukan, M. M., & Hazarika, N. (2020). Monitoring land use land cover changes in the Eastern Himalayan landscape of Nagaland, Northeast India. *Environmental Monitoring and Assessment, 192*(11), 711. https://doi.org/10.1007/s10661-020-08674-8

Silva, E. A., Tramontina, J., Alba, E., Goergen, L. C. de G., Finger, A. P., & Pereira, R. S. (2017). Forest Cover Analysis Through the Weights of Evidence Method in The Campanha Ocidental Region - Rs (Brazil). *Revista Árvore, 41*(1), e410105. https://doi.org/10.1590/1806-90882017000100005

Sinha, S., Mohan, S., Das, A. K., Sharma, L. K., Jeganathan, C., Santra, A., Santra Mitra, S., & Nathawat, M. S. (2020). Multi-sensor approach integrating optical and multi-frequency synthetic aperture radar for carbon stock estimation over a tropical deciduous forest in India. *Carbon Management, 11*(1), 39–55. https://doi.org/10.1080/17583004.2019.1686931

Torahi, A. A., Rai, S. C., Torahi, A. A., & Rai, S. C. (2011). Land Cover Classification and Forest

Change Analysis, Using Satellite Imagery-A Case Study in Dehdez Area of Zagros Mountain in Iran. *Journal of Geographic Information System, 3*(1), 1–11. https://doi.org/10.4236/JGIS.2011.31001

Yanapa, C. G. T., Sumerinde, L. D. V., Roman, I. O. C., & Catari, M. E. (2024). Analysis of Vegetation Cover Change with Satellite Images using Landsat 8 in the Inambari District in the Period 2013-2023. *Estudios y Perspectivas Revista Científica y Académica, 4*(1), 1124-1132. https://doi.org/10.61384/r.c.a.v4i1.150

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