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Assessing vegetation health and fragmentation in Aizawl District using Normalized Difference Vegetation Index

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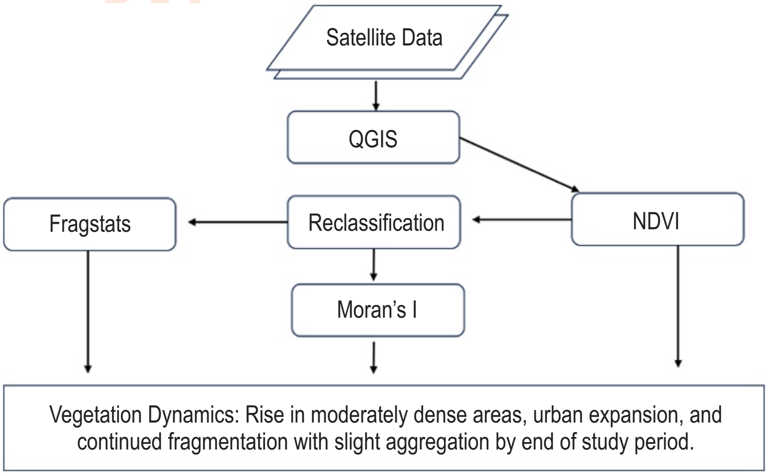
Abstract

Aim: To study the vegetation dynamics in Aizawl District, Mizoram, India, from 2013 to 2023, inorder to analyze the impact of urban expansion and reforestation efforts on forest cover and landscape fragmentation.



Vegetation Dynamics: Rise in moderately dense areas, urban expansion, and continued fragmentation with slight aggregation by end of study period.

Methodology: Landsat 8 imagery 8OLI/TIRS Collection 2 Level 1 and Level 2 from 2013, 2018 and 2023 was processed to calculate Normalized difference vegetation index (NDVI) in QGIS, then reclassified vegetation into density classes (non-vegetated area, sparse vegetation, slightly dense vegetation, moderately dense vegetation, and highly dense vegetation). Spatial autocorrelation, using Moran's I, assessed vegetation patterns, while Fragstats software quantified class and landscape metrics for spatial pattern analysis (Class metrics- PLAND, PD, ED, LSI, AI, and Landscape metrics-PD, LSI, SIDI, AI).

Results: Vegetation density fluctuated, initially declining from 2013 to 2018, and then recovering in 2023, according to NDVI analysis. Moderately dense vegetation class expanded 36.4% in 2013 to 42.8% in 2023 over the decade, while non-vegetated areas increased 3.2% in 2013 to 4.4% in 2023. Patch Density and Landscape Shape Index of the overall landscape indicate ongoing fragmentation, 65.47 and 333.102 in 2013 declining to 62.42 and 337.368 in 2018, though increased slightly to 72.03 and 322.992 by 2023. Simpson's Diversity Index (SIDI) rose from 0.7035 in 2013 to 0.7135 in 2018 before dropping to 0.6965 in 2023, indicating reduced landscape diversity and niche habitats, while the Aggregation Index (AI) increased from 63.14 to 64.04, reflecting reduced fragmentation and greater consolidation, particularly in moderately dense vegetation. Moran's I index followed a similar trend, decreasing from 0.679 in 2013 to 0.602 in 2018, and then rising back to 0.673 in 2023.

Interpretation: The findings suggest that urban expansion is a key driver of fragmentation, yet reforestation initiatives and minimal practice of shifting cultivation contribute to vegetation consolidation. Enhanced management strategies are recommended to preserve habitat connectivity and promote sustainable land use, supporting ecological resilience in Aizawl District.

Key words: Aizawl, Normalized Difference Vegetation Index, Remote sensing, Vegetation fragmentation

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Introduction

Changes in land cover, driven by both natural processes and human activities, significantly impact temporal and spatial availability along with distribution of environmental resources (Kumar *et al.,* 2014). These changes also influence the productivity, diversity and structure of ecosystems, altering ecological functions and services (Mancino *et al.,* 2014). Monitoring such changes is crucial for sustainable land management, biodiversity conservation and assessing the impacts of climate change. Remote sensing techniques have become indispensable tools for analyzing these spatial and temporal environmental shifts (Navalgund *et al.,* 2019). These techniques identify alterations in vegetation cover or other land-use types by capturing shifts in spectral attributes, reflecting biophysical changes, such as vegetation health, land degradation, or urban expansion (Zhu *et al.,* 2022; Rane *et al.,* 2023).

By comparing multi-temporal satellite images, remote sensing provides valuable insights into environmental transformations, helping to inform policy decisions and promote adaptive strategies. The health and density of vegetation are critical components of ecosystem stability and functionality, playing a vital role in maintaining biodiversity, regulating water cycle and providing necessary habitats for various species (Khan *et al.,* 2018; Garoonand Mule, 2023). Increased urban vegetation cover has been associated with improved air quality along with decreased heat-related effects, according to research (Leung *et al.,* 2011; Sussman *et al.,* 2019; Dardirand Berardi, 2022). The presence of more plants and greenery can improve air filtration, absorb heat and create cooler microclimates, thereby enhancing the overall environmental quality and resilience of metropolitan regions (Wang *et al.,* 2014; Yang *et al.,* 2014; Rawski, 2019). Therefore, monitoring vegetation health is beneficial for ecological studies and crucial for urban planning and public health assessments. Understanding these impacts on vegetation health becomes paramount as human activities increasingly lead to land-use changes and habitat fragmentation.

In recent years, monitoring vegetation patterns has immensely benefited by using remote sensing data (Bagaria *et al.,* 2021). The scientific community has had consistent data from satellite-based high-resolution observations using multispectral scanners in recent decades, which has allowed them to carry out extensive thematic mapping for land classification at local and regional scales (Lu and Weng, 2007; Friedl *et al.,* 2010; Giri, 2012). Rouse *et al.* (1973) developed NDVI emerged as pivotal tool in ecological research. It has been used to assess vegetation health and monitoring changes in land cover (Pettorelli *et al.,* 2005). NDVI is based on the principle healthy vegetation has low reflectance in the visible portion of the electromagnetic spectrum due to the absorption of pigments consisting of chlorophyll as well as elevated reflectance in the near-infrared (NIR) due to internal reflectance by the mesophyll spongy tissue of green leaves (Campbell, 1987). NDVI of a sensor system can be determined by calculating the ratio of red as well as NIR bands. The capability of NDVI to detect subtle changes in vegetation cover over time makes it invaluable for a variety of ecological applications, including agricultural monitoring (Choudhary *et al.,* 2019; Filgueiras *et al.,* 2019), forest health assessments (Wang *et al.,* 2010; Ivan *et al.,* 2018) and detection of environmental stress related to drought and flooding events (Sims and Colloff, 2012; Ahmed and Akter, 2017; Puletti *et al.,* 2019).

By facilitating long-term and short-term analysis of vegetation patterns, NDVI contributes to our understanding of ecological dynamics and offer insights how ecosystems respond to climatic and anthropogenic pressures. The ability to remotely observe vegetation changes enhances our comprehension of ecosystem dynamics as well as informs improved management practices for reducing environmental degradation (Smith *et al.,* 2014; Herbei *et al.,* 2016). Furthermore, NDVI complements ground-based assessments, facilitating a holistic view of vegetation conditions, which is crucial for sustainable land-use practices.

Fragmentation, on the other hand, refers to the process by which larger, contiguous habitats are divided into smaller, isolated patche (Haddad *et al.,* 2015). This phenomenon can result from agricultural expansion, urban development and infrastructure projects that disrupt the landscape (Pardini *et al.,* 2017). Fragmentation poses significant threats to biodiversity by creating barriers that hinder species movement, which can lead to population decline or extinction (Cordingley *et al.,* 2015; Wilson *et al.,* 2015). Furthermore, isolated patches may experience edge effects, where environmental conditions differ significantly from the interior of forest, increasing vulnerability to invasive species and altering microclimates (Murcia, 1995). Understanding fragmentation effects is critical, especially in socio-ecological systems where human activities intersect with natural landscapes.

Management of vegetation has become a critical priority to maintain ecological balance with the advancement of urbanization. Expansion of residential, commercial and infrastructural zones can negatively impact vegetation, leading to habitat fragmentation, loss of biodiversity and disruptions in ecosystem services (Güneralp *et al.,* 2013; Dai and Dai, 2019). Urban forestry is essential in resolving these issues by evaluating the status as well as scope of urban vegetation along with infrastructure while managing their growth and deterioration to minimize negative impacts (Gillespie *et al.,* 2012).

Aizawl District in Mizoram, India serves as an example of rapid urbanization, with considerable demographic shifts and infrastructural development. This study focuses on assessing vegetation health and fragmentation in Aizawl District, Mizoram. It analyses spatial patterns and temporal variations in vegetation cover as well as health spanning over a period of ten years, from 2013 to 2023, using NDVI. By examining these patterns, the present study explains how urbanization and land management practices have influenced vegetation dynamics, including potential habitat fragmentation, providing foundation for ecosystem management and sustainable urban planning.

Materials and Methods

Study area: The study was carried out in Aizawl District, Mizoram, India, across a ten-year span, with data analyzed for the years 2013, 2018 and 2023. Aizawl lies approximately between 23°30'N-23°50'N latitude and 92°40'E-92°55'E longitude (Fig. 1). The area covers 3,576 sq. km. characterized by hilly terrain, valleys and forested areas. It is the most populous district in Mizoram; as of 2011 Census of India, Aizawl District had a population of about 400,309, with urban population concentrated in Aizawl city and surrounding towns. The region has experienced significant demographic changes in recent years, driven by migration and urban expansion, contributing to rapid infrastructural development (Saitluanga, 2018). Aizawl District has a humid subtropical climate (Cwa under the Köppen climate classification) with distinct wet and dry seasons. Monsoon season, lasting from May-September, brings heavy rainfall, with average annual precipitation exceeding 2,500 mm. Temperature ranges between 11– 29°C throughout year, with cooler conditions prevailing during winter months from November to February (Government of Mizoram, 2022).

Data acquisition: Satellite imagery from Landsat 8 OLI/TIRS Level-1 and Level-2 data with a spatial resolution of 30 m and minimal cloud cover (≤10%) (Table 1), products from the Landsat 8 satellite's Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). These products are available for download from the USGS (.gov) and the ESA Landsat Online Dissemination Service (LOADS and SO-CAT systems). This medium-resolution data ensures accurate detection of land cover changes, providing reliable insights into vegetation dynamics and urban expansion.

QGIS 3.26.3, an open-source Geographic Information System, was employed for spatial data processing and analysis due to its versatility in handling geospatial data. Fragstats 4.2, a specialized tool for landscape metrics, was used to quantify landscape structure and analyze spatial patterns.These tools facilitate a comprehensive examination of land-use changes and their ecological implications.

Calculation of NDVI: Normalized Difference Vegetation Index (NDVI) was calculated using multispectral bands from the remote sensing imagery. The formula used for NDVI calculation is as follows:

$$NDVI=(NIR-Red)/(NIR+Red)$$

where, NIR corresponds to near-infrared band (Band 5) and Red corresponds to red band (Band 4) of Landsat 8 satellite imagery. This index ranges from-1 to 1, with higher values indicating healthier and denser vegetation. NDVI values were calculated for each period under study, facilitating the analysis of vegetation dynamics and fragmentation patterns over the ten years. The NDVI values for 2013, 2018, and 2023 were then reclassified as non-vegetated (–1.0 to 0.0), sparse vegetation (0.10–0.20), slightly dense vegetation (0.21–0.30), moderately dense vegetation (0.31–0.40), and highly dense vegetation (0.41–1.0).

Fragstats metrics and interpretation: We computed class- and landscape-level metrics of the reclassified NDVI in FRAGSTATS to quantify composition and configuration. Units: PD= patches/100 ha; ED= m/ha; AI= %; LSI= unitless; SIDI ranges 0–1.

Class-level:

Percentage of land (PLAND): Indicates the percentage of the landscape occupied by a specific land cover class, showing its dominance or rarity (McGarigal and Marks, 1995). Patch Density (PD): Measures the number of patches per 100 hectares, reflecting the degree of landscape fragmentation (Gustafson, 1998). Edge Density (ED): Represents the total edge length of a class per hectare, used to assess fragmentation and edge effects (McGarigal et al., 2002). Landscape Shape Index (LSI): Reflects patch shape complexity, with higher values indicating more irregular and fragmented shapes (Patton, 1975; McGarigal and Marks, 1995). Aggregation Index (AI): Indicates how clumped or dispersed patches of the same class are, with higher values showing greater aggregation (He et al., 2000).

Table 1: Characteristics of satellite data employed in research

ID	Path/Row	Date acquired (yy-mm-dd)	Sun elevation (degrees)	Band/Wavelength spectral range (µm)	Spatial resolution (m)
LC08_L1TP_136044_20131217_20200912_02_T1	135/43	2013-12-17	38.830	Band 4(0.630–0.680), 5(0.845-0.885)	30
LC08_L1TP_136043_20131217_20200912_02_T1	135/44	2013-12-17	37.632	Band 4(0.630–0.680), 5(0.845-0.885)	30
LC08_L2SP_136043_20181231_20200829_02_T1	136/43	2018-12-31	37.015	Band 4(0.630–0.680), 5(0.845-0.885)	30
LC08_L2SP_136044_20181231_20200829_02_T1	136/44	2018-12-31	38.178	Band 4(0.630–0.680), 5(0.845-0.885)	30
LC08_L1TP_136043_20231127_20231129_02_T1	136/43	2023-27-11	40.423	Band 4(0.630–0.680), 5(0.845-0.885)	30
LC08_L1TP_136044_20231127_20231129_02_T1	136/44	2023-27-11	41.630	Band 4(0.630–0.680), 5(0.845-0.885)	30

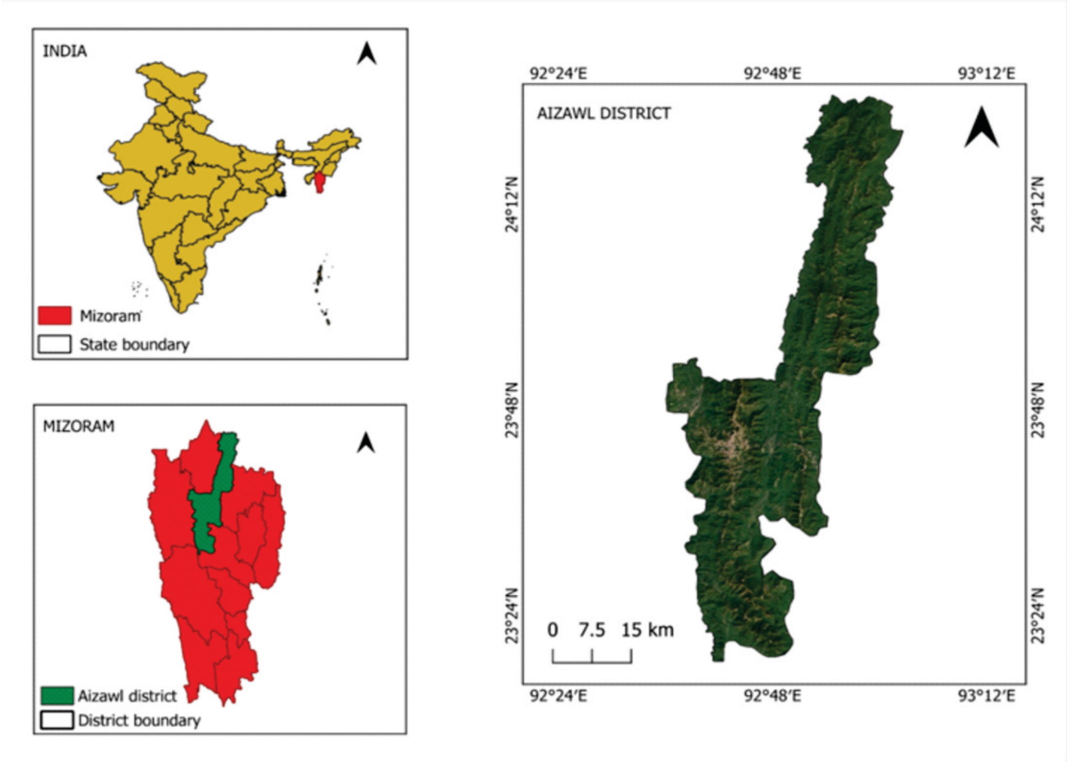

Fig. 1: Location map of the study area.

Landscape-level: Patch Density (PD): Indicates the number of patches per 100 hectares across the landscape, where higher values signify greater fragmentation (McGarigal et al., 2002). Landscape Shape Index (LSI): Reflects the complexity of patch shapes across the landscape, with higher values indicating more irregular and fragmented forms (Haines- Young and Chopping, 1996). Simpson's Diversity Index (SIDI): Quantifies the diversity of land cover types, with higher values representing greater richness and evenness (Simpson, 1949). Aggregation Index (AI): Measures the spatial clustering of similar patches, where higher values denote greater aggregation and lower fragmentation (He et al., 2000).

Spatial autocorrelation: Spatial autocorrelation is a statistical technique that measures the relationships between the given attribute and other surrounding areas in terms of a specific location. This statistical method allows predicting the degree of relatedness of attributes as well as spatial entities, including the pattern of distribution and spatial arrangement of the given attribute in geographical space. Also, spatial autocorrelation tests the hypothesis of positive/negative interdependence that exists between the attribute entity and the attribute values of its neighbouring entity (Jossart *et al.,* 2020). Spatial pattern and distribution of vegetation cover in Aizawl district were investigated in this research employing Moran's I index developed by Moran (1950). Based on the spatial autocorrelation analysis, it is possible to identify and study various spatial patterns in forest coverage. These patterns can play a crucial role in guiding policies and designing more effective strategies for managing vegetation and related issues. This global statistic enabled us to study more general spatial trends. Moran's I index ranges from +1, that represents positive spatial autocorrelation, to -1, indicating negative autocorrelation, while a zero represents no spatial correlation. The following equation explains Global Moran's I (Anselin, 1995):

$$\frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\omega_{ij}\,(x_i-X^{-})(x_j-X^{-})}{S^2\sum_{i=1}^{n}\sum_{j=1\omega ij}^{m}}$$

where, *n* represents the total number of spatial units, S^2 represents variance of attribute values, *xi* represents attribute value at location i, *Wij* represents spatial weight matrix defining relationships between spatial units

Results and Discussion

NDVI analysis revealed notable spatio-temporal variations in vegetation density from 2013 to 2023 (Table 2). The maximum NDVI value slightly decreased from 0.565 in 2013 to 0.549 in 2018, before increasing to 0.614 in 2023, indicating an overall improvement in vegetation density by the end of the study period. This positive change is likely due to afforestation programs such as the Green Mizoram Programme, which has facilitated the planting of over 3.6 million seedlings since 1999 (Government of Mizoram, 2016). Mean NDVI values reflected a similar trend, with a dip in 2018 followed by a recovery in 2023, supporting a decade-long enhancement in vegetation cover.

In contrast, the minimum NDVI values declined over time, with a significant drop to -0.214 in 2023 from -0.063 in 2013, suggesting expansion of non-vegetated or barren areas. This decline may be attributed to anthropogenic influences such as urbanization and agricultural expansion (Bai *et al.,* 2008; Wang *et al.,* 2022). The widening NDVI range from 2013 to 2023 points to increasing heterogeneity in land cover, characterized by simultaneous vegetation growth in some areas and degradation in others (Saikia, 2009; Nishant *et al.,* 2022). Vegetation class analysis (Table 3) revealed important structural changes. Moderately dense vegetation showed the most significant increase, with its share of PLAND rising from 36.4% in 2013 to 42.8% in 2023. Corresponding decrease in PD, ED, and LSI, alongside a rise in AI from 61.05 to 67.59, indicate consolidation of vegetation patches and improved ecological connectivity. This trend aligns with reduced shifting cultivation in the region, influenced by increased environmental awareness and land use policies (Sati and Rinawma, 2014; Kalita *et al.,* 2023). Slightly dense vegetation initially increased to 19.7% in 2018 but dropped to 11.96% by 2023. The increased fragmentation, indicated by higher PD and lower AI (33.39), suggests conversion of these areas into built-up or degraded land. Sparse vegetation gradually increased in PLAND from 7.3 to 10.2%, but rising PD and ED suggest these vegetated areas remain highly fragmented and ecologically disconnected (Banks-Leite *et al.,* 2020). Highly dense vegetation declined slightly in PLAND from 35.6% to 30.6%, likely due to land clearing and development. However, high AI (~77) throughout indicates continued patch aggregation, emphasizing the importance of protecting these zones for biodiversity. Non-vegetated areas increased modestly from 3.2 to 4.4%, with rising PD and ED values and increased LSI, suggesting more irregular and fragmented non-vegetated patches.

Table 2: NDVI values

Year	Maximum NDVI	Minimum NDVI	Mean NDVI	NDVI Range
2013	0.565	-0.063	0.251	0.629
2018	0.549	-0.054	0.247	0.604
2023	0.614	-0.214	0.2	0.828

Table 3: Class metrics

Vegetation Class	PLAND (%)			PD (No./100 ha)			ED (m ha^{-1})			LSI			AI (%)		
	2013	2018	2023	2013	2018	2023	2013	2018	2023	2013	2018	2023	2013	2018	2023
Moderately Dense Vegetation	36.44	37.76	42.83	15.03	13.94	9.85	140.14	139.31	133.53	340.01	333.95	308.12	61.05	62.34	67.59
Slightly Dense Vegetation	17.45	19.73	11.96	21.93	21.05	31.76	99.46	105.38	88.23	322.96	325.06	334.07	46.52	49.27	33.39
Sparse Vegetation	7.32	8.3	10.24	14.51	13.81	15.09	44.73	46.08	60.65	235.05	234.67	252.97	39.86	43.55	45.57
Highly Dense Vegetation	35.63	31.17	30.55	10.11	10.19	9.94	75.3	70.48	66.56	189.16	187.96	182.36	78.14	76.73	77.34
Non-Vegetated Area	3.16	3.04	4.42	3.89	3.42	5.39	10.35	8.55	18.32	93.83	86.08	112.29	63.67	65.97	63.33

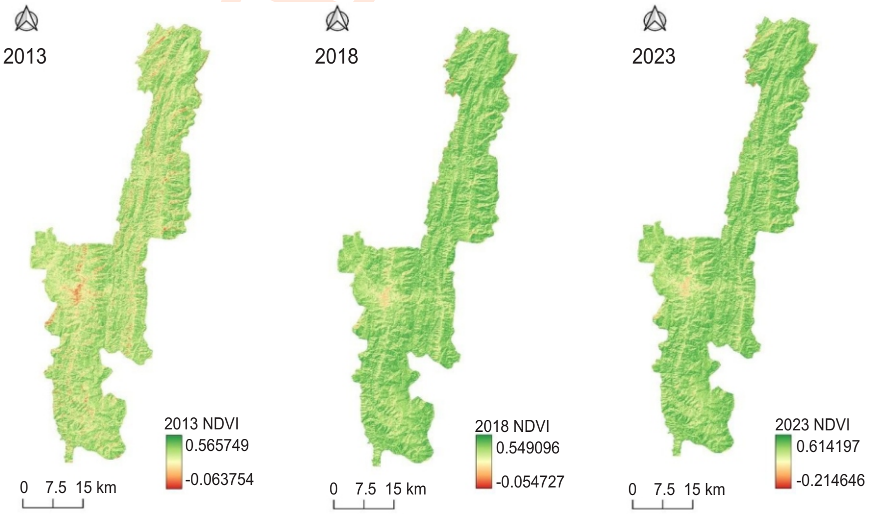

Fig. 2: NDVI of 2013, 2018 and 2023.

Table 4: Landscape metrics

Year	PD (Number(patches) (100 ha)$^{-1}$)	LSI	SIDI	AI (%)
2013	65.47	333.102	0.7035	63.14
2018	62.42	337.368	0.7135	62.80
2023	72.03	322.992	0.6965	64.04

Table 5: Moran's I value for 2013, 2018 and 2023

Year	Moran's I Index	Z-score	P value
2013	0.679245	23.5837	0
2018	0.602299	25.01292	0
2023	0.672929	21.8069	0

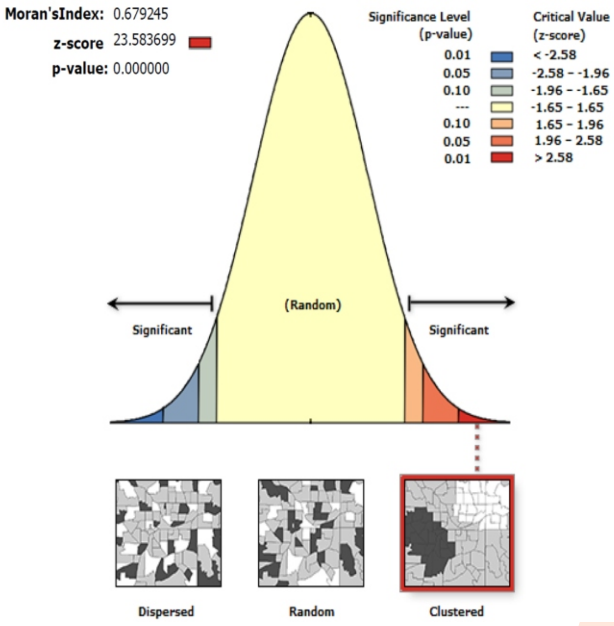

Fig. 3: Moran's I for 2013

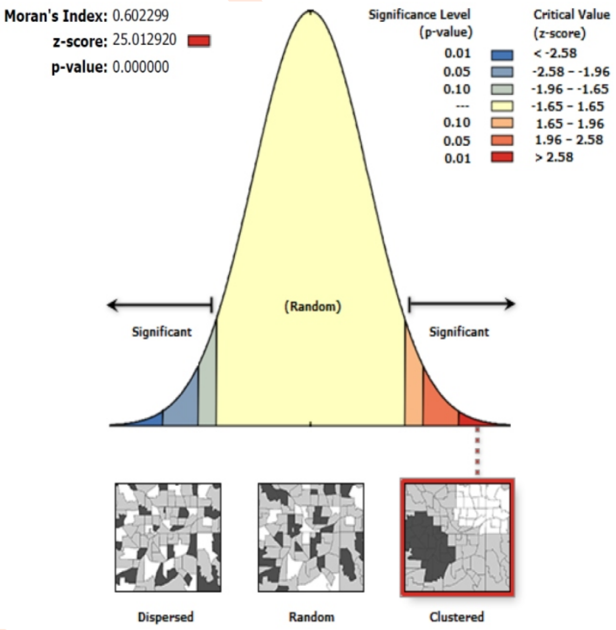

Fig. 4: Moran's I for 2018

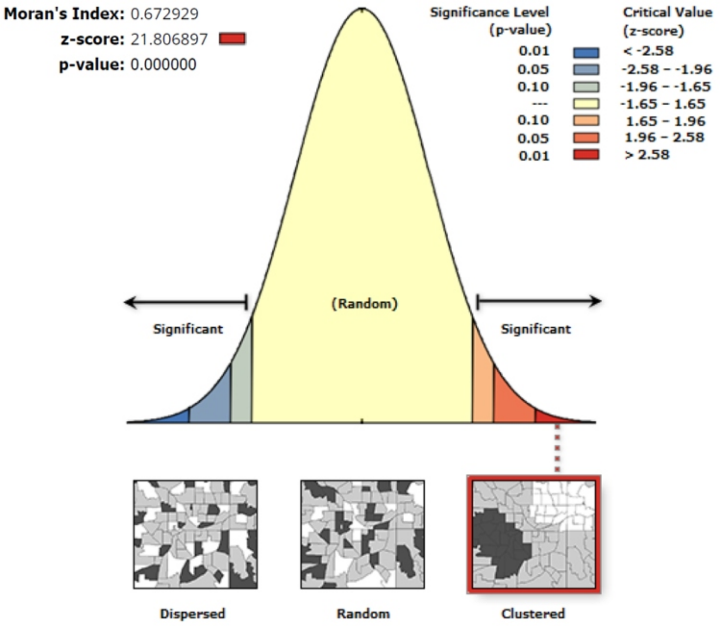

Fig. 5: Moran's I for 2023

Landscape-level metrics (Table 4) reinforce these patterns. PD decreased from 65.47 in 2013 to 62.42 in 2018 but rose to 72.03 in 2023, indicating increased fragmentation, likely due to urban encroachment. The LSI peaked at 337.37 in 2018 before reducing to 322.99 in 2023, reflecting a trend toward more compact patch shapes that may reduce edge effects (Laurance *et al.,* 2007). SIDI increased slightly to 0.7135 in 2018 but decreased to 0.6965 in 2023, suggesting decreasing landscape diversity due to dominance of specific vegetation classes. Conversely, AI increased from 63.14 to 64.04 over the decade, indicating a trend toward patch consolidation, especially in moderately dense areas, which could improve habitat stability.

Spatial autocorrelation (Table 5, Fig. 3,4 and 5) revealed consistently positive and statistically significant values (0.679 in 2013, 0.602 in 2018, and 0.673 in 2023), confirming a highly clustered spatial pattern throughout the study period. The dip in 2018 followed by a rebound in 2023 may reflect temporary shifts in land use or policy impacts (Meiyappan *et al.,* 2016; Zhang *et al.,* 2022). Investigating external contextual factors or local policy changes that could impact spatial distributions over time would be necessary to understand these dynamics. Despite fluctuations, the p-values (<0.05) and z-scores (>2.58) in all years confirm the robustness of spatial auto correlation. The high z-score in 2018, despite a lower Moran's I value, indicates a less intense but more statistically confident clustering pattern. These trends underscore persistent non-random spatial vegetation distribution, influenced by both ecological recovery and anthropogenic pressures. The landscape of Aizawl District has been shifting in ways that reflect both natural re-growth and mounting land use pressures. The increase in moderately dense vegetation and aggregation indices is promising, as these changes can improve habitat continuity and support biodiversity. However, the decline in mild dense and high dense vegetation, along with increased fragmentation in sparse vegetation, points to challenges to ecological connectivity.

Beyond land use, interannual climate variability may also have influenced vegetation patterns in Aizawl District. Fluctuations in rainfall, temperature, and extreme weather events could have impacted vegetative growth and contributed to NDVI variability over the decade. While this study focused on land cover metrics, integrating climatic datasets in future research would help disentangle the roles of natural versus anthropogenic drivers of vegetation change. The observed structural shifts, such as increased aggregation of moderately dense vegetation and fragmentation of slightly dense and sparse vegetation, have implications for ecosystem services.

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Authors' contribution: R. Lalruatdika: Conceptualization, execution of work, drafting of manuscript; **Zoramkhuma:** Data analysis and writing; **S. Nandy:** Guidance and manuscript correction; **K.C. Das:** Supervision of research work and manuscript correction.

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Data availability: The dataset employed in this research can be obtained from the corresponding author upon request.

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