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Tracing Pollution Footprints: A Spatio-Temporal Remote Sensing Study of Urban Growth and Road Expansion in Bhiwadi (2016-2025)

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सार – पिछले दशक में औद्योगीकरण में वृद्धि के कारण भिवाड़ी में तीव्र विकास एवं विस्तार हुआ है, जिसके परिणामस्वरूप राष्ट्रीय राजधानी क्षेत्र (NCR) में भूमि उपयोग में महत्वपूर्ण परिवर्तन हुए हैं और क्षेत्र की प्रदूषण के प्रति संवेदनशीलता बढ़ी है। इस अध्ययन में पिछले दस वर्षों के दौरान सेंटिनल-2 (Sentinel-2) उपग्रह चित्रों, सामान्यीकृत अंतर वनस्पति सूचकांक (NDVI)/सामान्यीकृत अंतर निर्मित सूचकांक (NDBI) तथा के-औसत क्लस्टरिंग आधारित भूमि उपयोग एवं भूमि आवरण (K-means LULC) वर्गीकरण का उपयोग करके निर्मित क्षेत्र में वृद्धि, वनस्पति में कमी, बंजर भूमि में वृद्धि तथा सड़क नेटवर्क के विस्तार का अध्ययन किया गया। अध्ययन में पाया गया कि निर्मित क्षेत्र 89.86 वर्ग किमी से बढ़कर 117.51 वर्ग किमी हो गया, जो 30.8% की वृद्धि है। वनस्पति क्षेत्र 173.0 वर्ग किमी से घटकर 141.7 वर्ग किमी रह गया, अर्थात् 18.1% की कमी हुई, जबकि बंजर भूमि 8.77 वर्ग किमी से बढ़कर 22.92 वर्ग किमी हो गई, जो 161% की वृद्धि है। सड़क नेटवर्क की लंबाई 409.78 किमी से बढ़कर 616.72 किमी हो गई, अर्थात् 50.5% की वृद्धि हुई। वर्ष 2018 के बाद रेलवे कॉरिडोर के निर्माण से औद्योगिक विकास तथा परिवहन-संबंधी उत्सर्जन में और वृद्धि हुई। LULC अध्ययन से यह भी पता चला कि 2016 से 2025 के बीच लगभग 42.5% वनस्पति क्षेत्र नष्ट हुआ, जबकि निर्मित क्षेत्र में कुल लगभग 26.1% की वृद्धि हुई। अधिकांश विकास उत्तरी-मध्य भाग तथा औद्योगिक कॉरिडोर में हुआ। अध्ययन के वर्गीकरण की सटीकता भी उच्च रही, जो 2016 के लिए 88.66% तथा 2025 के लिए 87.33% थी। स्थानिक ओवरले से “हॉट स्पॉट” अर्थात् ऐसे “त्रि-प्रभाव” वाले क्षेत्रों की भी पहचान हुई, जहाँ वनस्पति की हानि, सड़क घनत्व और तीव्र निर्माण गतिविधियाँ एक साथ केंद्रित हैं तथा जिनके प्रदूषण से प्रभावित होने की संभावना अधिक है। निष्कर्षों से संकेत मिलता है कि भारत के सर्वाधिक वायु-प्रदूषित औद्योगिक शहरों में से एक भिवाड़ी में अवसंरचना-आधारित शहरीकरण के भविष्य के पर्यावरणीय प्रभावों को कम करने के लिए वनस्पति बफर विकसित करना, धूल नियंत्रण की रणनीतियाँ अपनाना तथा परिवहन के स्वच्छ साधनों को सुनिश्चित करना आवश्यक है।

ABSTRACT. Bhiwadi has seen tremendous growth and development in the last decade with the increase of industrialisation leading to significant land transformation in the NCR, increasing its susceptibility to pollution. This study investigated the increase in built-up areas, the decrease in vegetation, the increase in bare land, and the increase in the road network using Sentinel-2 images, NDVI/NDBI indices and K-means LULC classification over the past ten years. The study found an increase in built-up areas from 89.86 km² to 117.51 km² (30.8%), a decrease in vegetation from 173.0 km² to 141.7 km² (18.1%), and an increase in bare land from 8.77 km² to 22.92 km² (161%). The length of the road network increased from 409.78 km to 616.72 km (50.5%) and was further increased by the construction of the railway corridor after 2018 which increased industrial development and the transportation-related emissions. The LULC study also shows that between 2016 and 2025, approximately 42.5% of vegetation was lost, whereas, built-up areas increased by a total of approximately 26.1% during the same period, and that the majority of the developed area occurred in the north-central and industrial corridors. The study's classification accuracy was also high with 88.66% accuracy for 2016 and 87.33% accuracy for 2025. The results of the spatial overlays also provided examples of "hot spots", or areas of "triple-impacts" where vegetation loss, high road density and rapid construction all converge and are likely more susceptible to being impacted by pollution. These findings indicate that for Bhiwadi as one of India's worst air polluted industrial cities, to mitigate the future environmental effects of urbanisation as a result of infrastructure, it is essential to create vegetation buffers, provide dust-control strategies, and ensure cleaner modes of transport.

Key words – Land use/Land cover (LULC), Normalized difference built-up index (NDBI), Normalized difference vegetation index (NDVI), Urban planning, National capital region (NCR).

1. Introduction

Air pollution is among the most serious environmental issues facing regions of rapid urbanization and industrialization (Singh *et al.*, 2020; Mandal *et al.*, 2024; Saha *et al.*, 2024). Areas experiencing rapid industrialization often contend with a preponderance of vehicle emissions, industrial waste, and airborne dust, raising PM_{2.5}, PM₁₀, NO₂, SO₂, and VOCs to levels of concern (Waqas *et al.*, 2024; Mogno *et al.*, 2023). Land-use / land-cover (LULC) change complexity pollution dynamics by changing sources of emissions, changing wind flow in the urban canopy, and reducing vegetated sinks for pollution (Oke, 1988; Pugh, *et al.*, 2012; Abhijith *et al.*, 2017; Janhäll, 2015; Duan *et al.*, 2022). In industrial towns, built-up area expansion, area increase road networks, and vegetation loss are directly linked to poor air quality (Badach *et al.*, 2020; Bala *et al.*, 2024; Mueller *et al.*, 2022; Singh *et al.*, 2024; Yao *et al.*, 2025). Bhiwadi, that has become a major industrial hub in the past decade (RIICO, n.d.; Govt. of Rajasthan, 2023), is a prime example of one such urban pollution and land-use nexus. Multiple assessments rank Bhiwadi among India's most polluted cities, with annual PM_{2.5} far exceeding India's NAAQS (CPCB, 2009; IQAir, 2024; The Wire, 2023). Emissions from industrial point sources, high-density road traffic, and construction activities, combined with rapid built-up expansion and road densification, severely limit pollutant dispersion within the urban canopy layer. Satellite-based remote sensing allows for consistent spatiotemporal monitoring of urban morphological changes and associated air pollution dynamics over multi-year timescales (Gorelick *et al.*, 2017; Nasiri *et al.*, 2022). The Normalized Difference Built-up Index (NDBI) highlights impervious surfaces (Zha *et al.*, 2003), while NDVI quantifies vegetation cover associated with pollutant removal and micro-climate regulation (Tucker, 1979; Duan *et al.*, 2022; Lai *et al.*, 2020). Together, NDBI and NDVI reveal trade-offs between urban expansion and green infrastructure that affect pollution vulnerability (Bala *et al.*, 2024; Wróblewska *et al.*, 2021; Mueller *et al.*, 2022).

The configuration and density of the road network are particularly important in the context of air quality. Roads act as linear emission corridors, higher road density and traffic volumes are consistently associated with elevated NO₂/PM (Waqas *et al.*, 2024; Mogno *et al.*, 2023). Sentinel-2 standard false-colour composites (NIR-Red-Green) make linear features conspicuous for accurate digitization (Sentinel Hub Scripts, n.d.; Nasiri *et al.*, 2022). Road-density mapping, combined with LULC change, identifies zones where vehicular emissions intensify particularly along growing industrial corridors (TERI/NCAP case evidence; Waqas *et al.*, 2024).

In this study, LULC classification is performed using an unsupervised K-means clustering approach. Given limited ground truth in mixed-use towns, unsupervised K-means is suitable for annual LULC mapping and reproducible monitoring (Gorelick *et al.*, 2017; Paradis *et al.*, 2022; Nasiri *et al.*, 2022). K-means partitions pixels into spectral clusters without pre-defined labels; auxiliary indices (NDVI, NDBI) improve separability of vegetation, bare soil, cultivated land, built-up, and water body (Zha *et al.*, 2003; Tucker, 1979). Post-classification visual checks w Standard False-Color Composite (SFCC) and high-resolution base maps help assign themes and correct edge artefacts before area statistics (Nasiri *et al.*, 2022). The present research integrates multi-temporal Sentinel-2 (2016-Feb 2025), NDBI/NDVI analysis, SFCC-based road mapping, and K-means classification to evaluate built-up expansion, road densification, and LULC transitions, with emphasis on the north-central corridor where a railway (operational since ~2018) and clustered industries produced a high-density emission zone (Govt. of Rajasthan, 2023; RIICO, n.d.). Findings support urban planning and pollution mitigation by explicitly linking LULC change to the spatial context of emission generation and dispersion in Bhiwadi/NCR (CAQM/CPCB, 2024; Mandal *et al.*, 2024).

2. Data and methodology

2.1. Study area

Bhiwadi, located in the Alwar district of Rajasthan, India, lies within the National Capital Region (NCR) and is one of the fastest-growing industrial towns in northern India (RIICO, n.d.). Geographically, the city extends between approximately 27°38'N to 27°41'N latitude and 76°49'E to 76°54'E longitude, covering an area of around 100 km² shown in Fig 1. Its strategic location, about 70 km southwest of Delhi and 40 km from Gurugram, has made it a preferred industrial destination, fostering rapid urbanization and infrastructural expansion over the past two decades (Govt. of Rajasthan, 2023).

Bhiwadi's climate is classified as semi-arid under the Köppen climate classification, characterized by hot summers, mild winters, and low annual rainfall averaging around 600-700 mm, most of which occurs during the monsoon months (July-September). The topography is generally flat with gentle undulations, which facilitates urban sprawl but also limits natural ventilation, thereby influencing pollutant dispersion patterns. (CPCB/IMD references; Oke, 1988). Economically, Bhiwadi hosts a diverse industrial base, including steel manufacturing, automobile assembly, textiles, chemicals, and plastics. The Bhiwadi Industrial Area, managed by the Rajasthan State Industrial Development and Investment Corporation

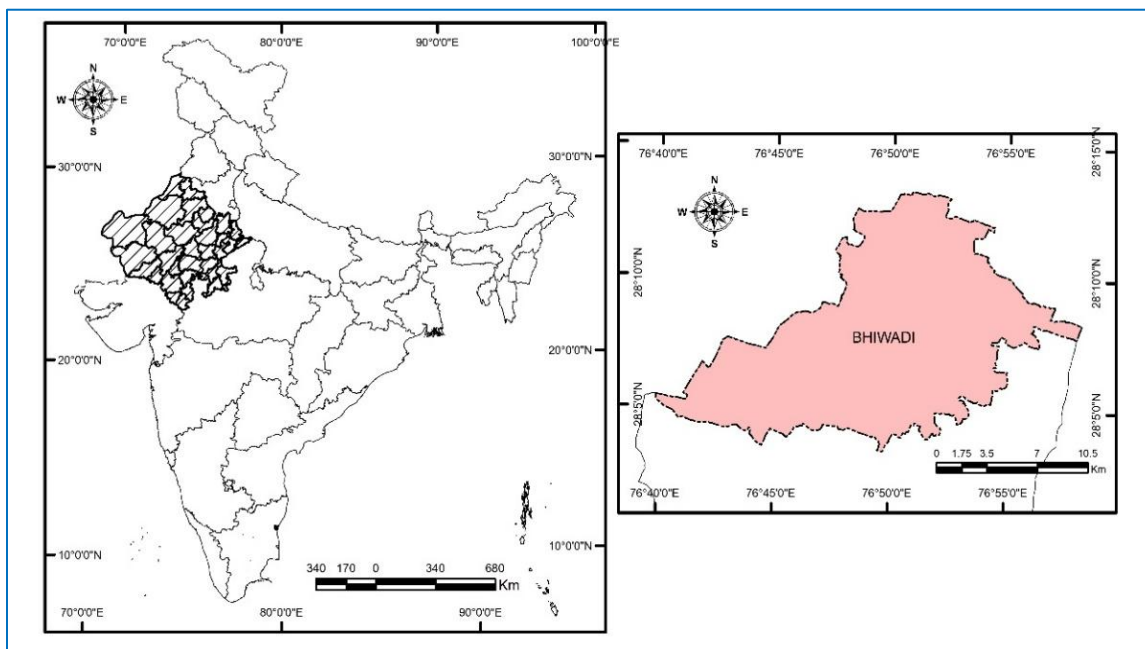


Fig. 1. Location map of the study area showing Bhiwadi town within Alwar district, Rajasthan, India

(RIICO), houses hundreds of large and medium-scale industries. This concentration of industrial activity, combined with high vehicular traffic along major corridors such as NH-48 and the newly developed railway line contributes significantly to local air pollution levels. (RIICO, n.d.; Govt. of Rajasthan, 2023).

From an environmental standpoint, Bhiwadi has often been identified as one of India's most polluted cities by the Central Pollution Control Board (CPCB). Different high levels of $PM_{2.5}$, PM_{10} , NO_2 , and SO_2 have been observed throughout the year, especially in winter months, when poor air quality is exacerbated by temperature inversions and lower wind speeds. Vegetation loss and the conversion of farmland into impervious built-up area have aggravated the issue by decreasing natural sinks of pollutants (CPCB, 2009; IQAir, 2024; Singh *et al.*, 2020; Duan *et al.*, 2022). Due to its rapid change and environmental susceptibility, Bhiwadi represents a unique case study for assessing the relationship between urbanization, land-use change, and expansion of the road network with pollution processes. The combination of imaging from Sentinel-2 satellites, geospatial analysis, and field observations supports monitoring of these changes from 2016-2025, and particularly from the north-central corridor where industrial development & transport infrastructure expansion have been most significant.

2.2. Methodology

This study follows a methodological framework that combines multi-temporal remote sensing analysis,

geospatial processing, and spatial statistics to investigate urban growth, road network expansion, land use change, and pollution potential in Bhiwadi from 2016 to February 2025. The workflow combines Sentinel-2 satellite imagery processed in Google Earth Engine (GEE), manual digitization and geoprocessing conducted in ArcMap, and final qualitative and quantitative analysis in Microsoft Excel shown in Fig 2.

2.2.1. Data Selection and Pre-Processing

The primary dataset in this study involves Sentinel-2 Level-1C imagery for its high spatial resolution, extensive spectral coverage, and frequent revisit cycle, all of which are advantageous for assessing rapid urban change and environmental effects. Each Sentinel-2 satellite collects 13 spectral bands - four bands at 10 m (Blue, Green, Red, NIR), and five bands at 20 m (2 Red Edge, SWIR 1, SWIR 2) that are useful for land cover discrimination. For this study, imagery for January and February of each year was extracted to mitigate seasonal variation in vegetation and standardize atmospheric conditions. The following thresholds for cloud cover, were established at <30% cloud cover, as median composites were constructed to suppress the impact of cloud cover and other transient noise (Nasiri *et al.*, 2022). Sentinel-2 was also selected as the study dataset in part because it is freely available and supports reproducibility and multiple years of data collection for analysis without front-end costs of data acquisition. Additionally, because it has a high revisit frequency (5 days with both satellites in the

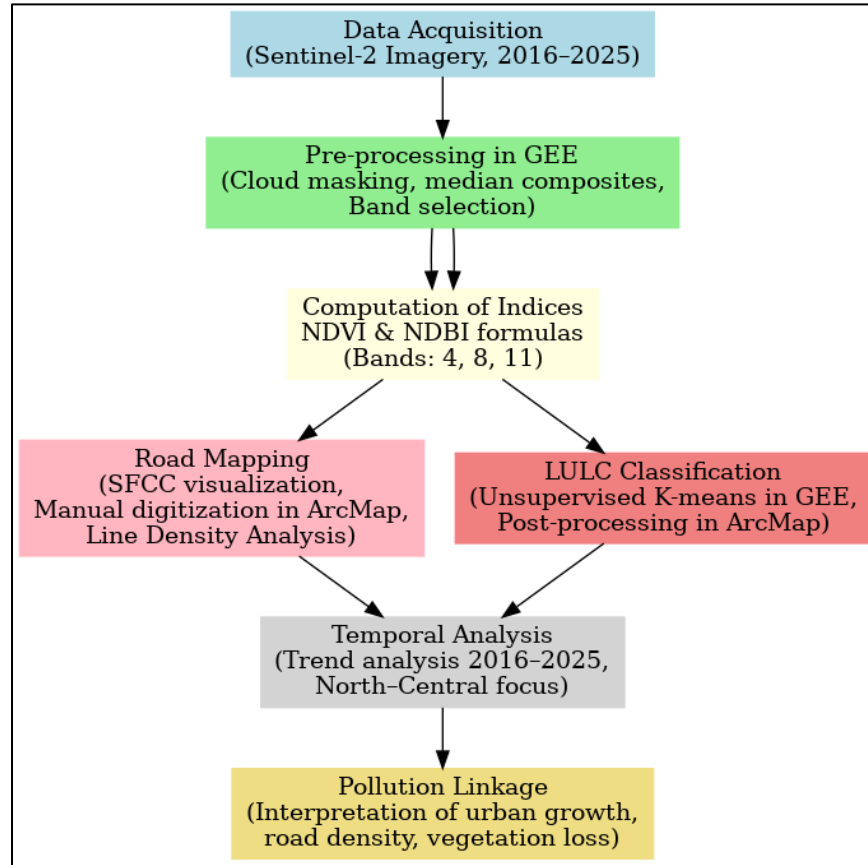


Fig. 2. Methodological workflow for spatio-temporal analysis of urban growth

operational scan rotation) it helps support needed temporal consistency critical for evaluating small changes in polluted urban landscapes from year to year.

2.2.2. Computation of Spectral Indices

In order to derive thematic information related to pollution-related urban change, two spectral indices were calculated:

Normalized Difference Vegetation Index (NDVI), a measure of vegetation health and density, calculated using the formula:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

where NIR = Band 8 (10 m, ≈ 842 nm) and Red = Band 4 (10 m, ≈ 665 nm). Higher NDVI values indicate greater health or density of vegetation, which is a crucial variable in air pollution absorption (Tucker, 1979).

Normalized Difference Built-up Index (NDBI) was then calculated to further delineate built-up and impervious areas, using the formula.

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad (2)$$

where SWIR = Band 11 (20 m, ≈ 1610 nm) and NIR = Band 8. Band 8 was resampled at 20 m to match the spatial resolution of SWIR (Duan *et al.*, 2022; Abhijith *et al.*, 2017). NDBI values correspond to built-up roofs and impervious surfaces that are directly related to vehicular traffic, industrial emissions, and urban heat setting that exacerbate pollution (Zha *et al.*, 2003).

2.2.3. Road Network Extraction and Density Analysis

Road mapping was performed using Standard False Colour Composite (SFCC) imagery from Sentinel-2, assigning Band 8 (NIR) to red, Band 4 (Red) to green, and Band 3 (Green) to blue. In SFCC, roads and other impervious surfaces appear as distinct light grey or cyan tones, enabling accurate identification even in densely built environments. Roads for 2016 and 2025 were manually digitized in ArcMap at a consistent scale to capture both primary and secondary networks (Sentinel Hub Scripts, n.d.; Nasiri *et al.*, 2022). The newly established railway line in 2018 was also mapped, as it

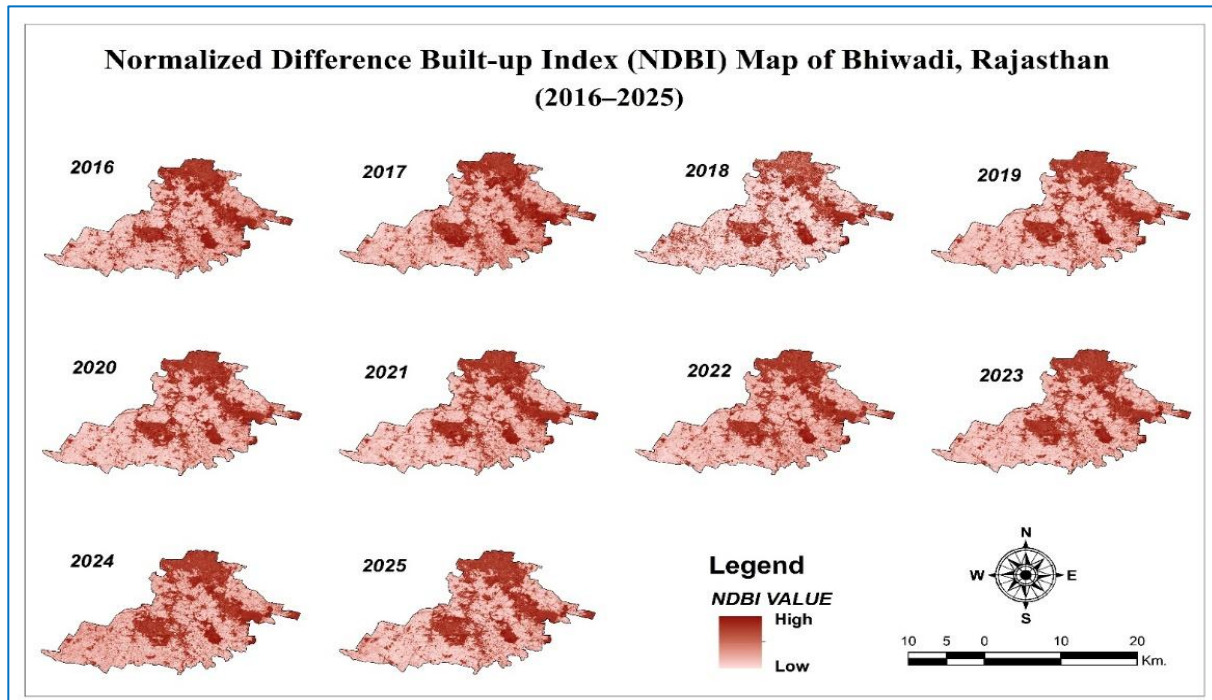


Fig. 3. Spatial distribution and decadal change in Normalized Difference Built-up Index (NDBI) depicting urban expansion in Bhiwadi from 2016 to 2025

significantly influenced subsequent road densification. The Line Density tool in ArcGIS was used to calculate road density in km/km^2 , producing spatially continuous surfaces that highlight changes in transportation corridors. Increased road density, particularly in the north and central industrial zones, was interpreted as a key driver of local air pollution due to higher vehicular emissions (Waqas *et al.*, 2024; TERI/NCAP case evidence; Mogno *et al.*, 2023).

2.2.4. Land Use/Land Cover (LULC) Mapping

LULC classification was performed using Unsupervised K-means clustering in GEE. This algorithm partitions the image into clusters by minimizing intra-cluster variance, making it suitable for areas like Bhiwadi where ground-truth data is limited. Five thematic classes were targeted: vegetation, bare land, cultivated land, built-up, and water bodies (Gorelick *et al.*, 2017; Zha *et al.*, 2003; Tucker, 1979; Paradis *et al.*, 2022). NDVI and NDBI layers were included as auxiliary inputs to enhance class separability.

The advantages of K-means for this study include:

- No dependence on extensive training data, enabling consistent classification across multiple years.
- Adaptability to spectral variability caused by seasonal and atmospheric differences.

- Objectivity and reproducibility, reducing user bias.

Post-classification, thematic labels were assigned through visual interpretation and cross-referencing with SFCC imagery and high-resolution Google Earth base maps (Nasiri *et al.*, 2022). The classified maps were then exported to ArcMap for spatial refinement, where edge misclassifications were corrected. Class areas were calculated annually and compiled in Excel for temporal trend analysis.

Accuracy assessment of the classified LULC maps for 2016 and 2025 was carried out using the Spatial Analyst tools available in ArcGIS Pro. Stratified random samples were generated using the Create Accuracy Assessment Points tool, which distributes points proportionally across all mapped classes and automatically records the class value extracted from the classified raster (ESRI, 2023). A total of 150 points were generated for each year to ensure adequate representation of built-up, cultivated land, bare land, vegetation, and water classes. The reference (ground-truth) labels for each point were manually assigned using high-resolution Google Earth imagery and Sentinel-2 FCC composites, following standard visual interpretation principles (Congalton & Green, 2009).

The reference class and the classified class were then compared using the Compute Confusion Matrix tool

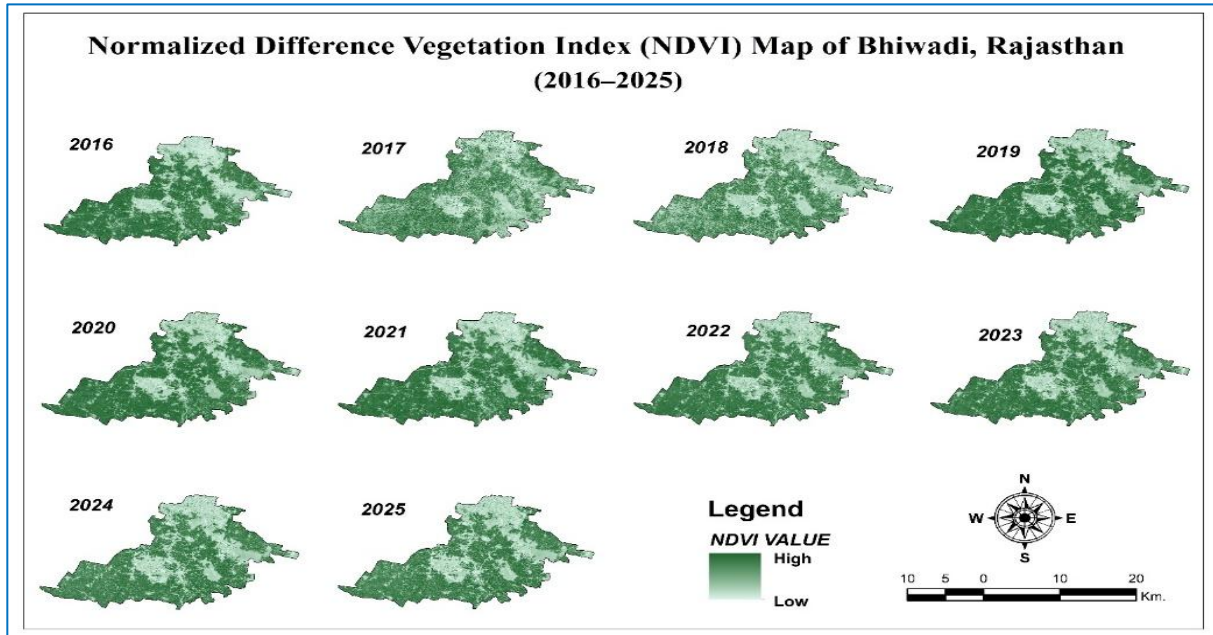


Fig. 4. Spatial distribution and decadal change in Normalized Difference Vegetation Index (NDVI) illustrating vegetation cover dynamics in Bhiwadi from 2016 to 2025



Figs. 5(a-c). (a) Annual variation in Normalized Difference Built-up Index (NDBI) for Bhiwadi from 2016 to 2025, (b) Annual variation in Normalized Difference Vegetation Index (NDVI) for Bhiwadi from 2016 to 2025 & (c) Correlation plot between NDBI and NDVI values (2016–2025) illustrating the inverse relationship between built-up expansion and vegetation cover decline

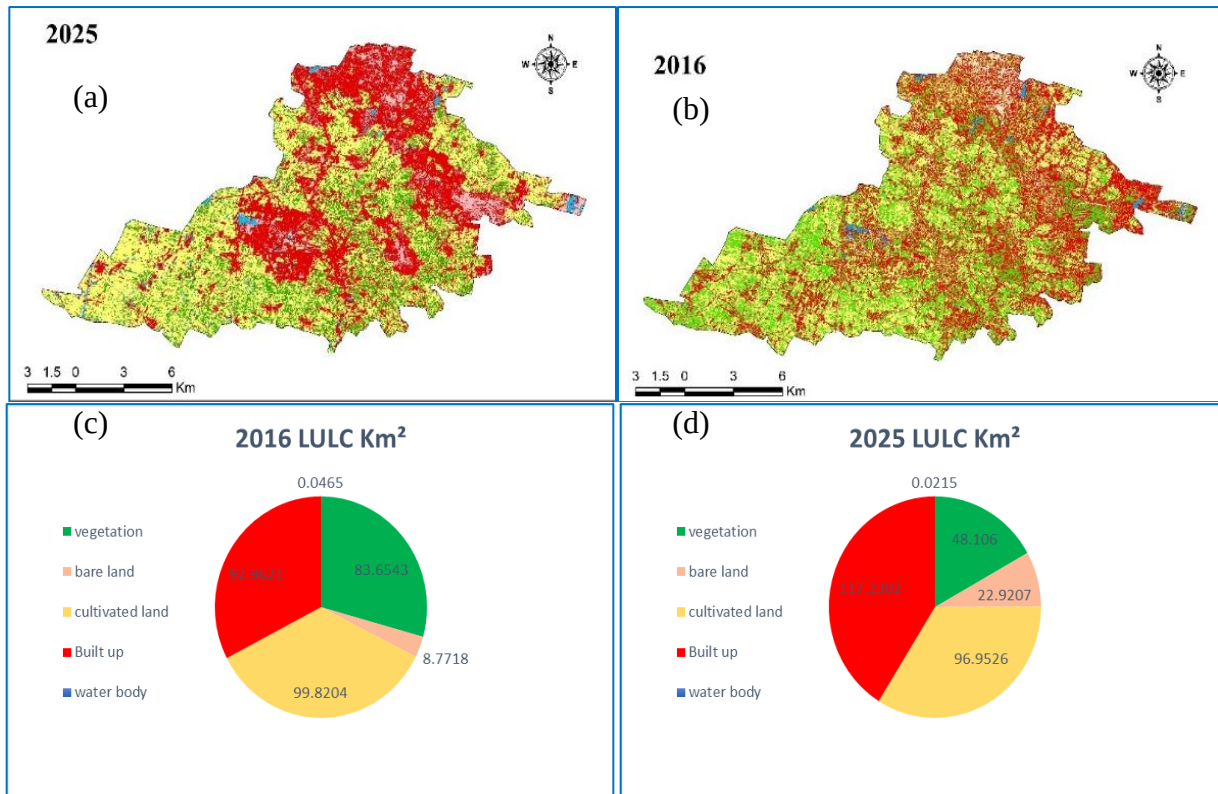


Fig 6. (a-d). (a-b) Land use/land cover (LULC) classification maps of Bhiwadi for 2016 and 2025 & (c-d) Class-wise area distribution of major LULC categories in 2016 and 2025 represented as comparative pie charts

in ArcGIS, which produces a full error matrix along with Producer's Accuracy (PA), User's Accuracy (UA), Overall Accuracy, and the Kappa coefficient. These metrics quantify the reliability of the classification and the degree of agreement beyond chance (Stehman, 1997; Foody, 2002). The resulting accuracy statistics for both 2016 and 2025 confirm that the K-means clustering approach produced robust LULC outputs suitable for subsequent spatio-temporal change analysis.

2.2.5. Temporal Analysis and Data Integration

The processed NDBI, NDVI, road density, and LULC datasets were analyzed for spatial patterns and temporal trends. Statistical summaries were generated for each parameter, and maps were visually interpreted to identify areas of significant change. (Bala *et al.*, 2024; Waqas *et al.*, 2024; Oke, 1988; CAQM/CPCB, 2024) Special emphasis was placed on the north-central industrial corridor, where built-up expansion, road densification, and vegetation loss were most pronounced. To contextualize exceedances, we refer to India's NAAQS (PM_{2.5} annual = 40 µg m⁻³) and recent India-wide PM_{2.5} surfaces (CPCB, 2009; Singh *et al.*, 2021; Mandal *et al.*, 2024). These spatial trends were linked to potential

increases in pollution emissions, supporting the broader environmental focus of the study.

3. Results and discussion

3.1. Urban Growth and Vegetation Dynamics (NDBI–NDVI Analysis)

The spatio-temporal analysis of NDBI values between 2016 and 2025 indicates a clear and sustained trend of urban expansion within Bhiwadi's municipal and industrial zones shown in Fig 3. The built-up area increased from 89.86 km² in 2016 to 117.51 km² in 2025, marking a net gain of 27.65 km² over the study period. This represents a ~30.8% increase in built-up extent, a rate considerably higher than the average urban growth rate reported for other Tier-II industrial towns in northern India during the same period. Spatially, the most pronounced changes occurred between 2016 and 2017, where the central urban core experienced densification and expansion towards the southern industrial belt. This phase corresponds with the establishment and expansion of multiple industrial estates under the Delhi-Mumbai Industrial Corridor (DMIC) influence, suggesting a strong policy-infrastructure nexus driving urban growth.

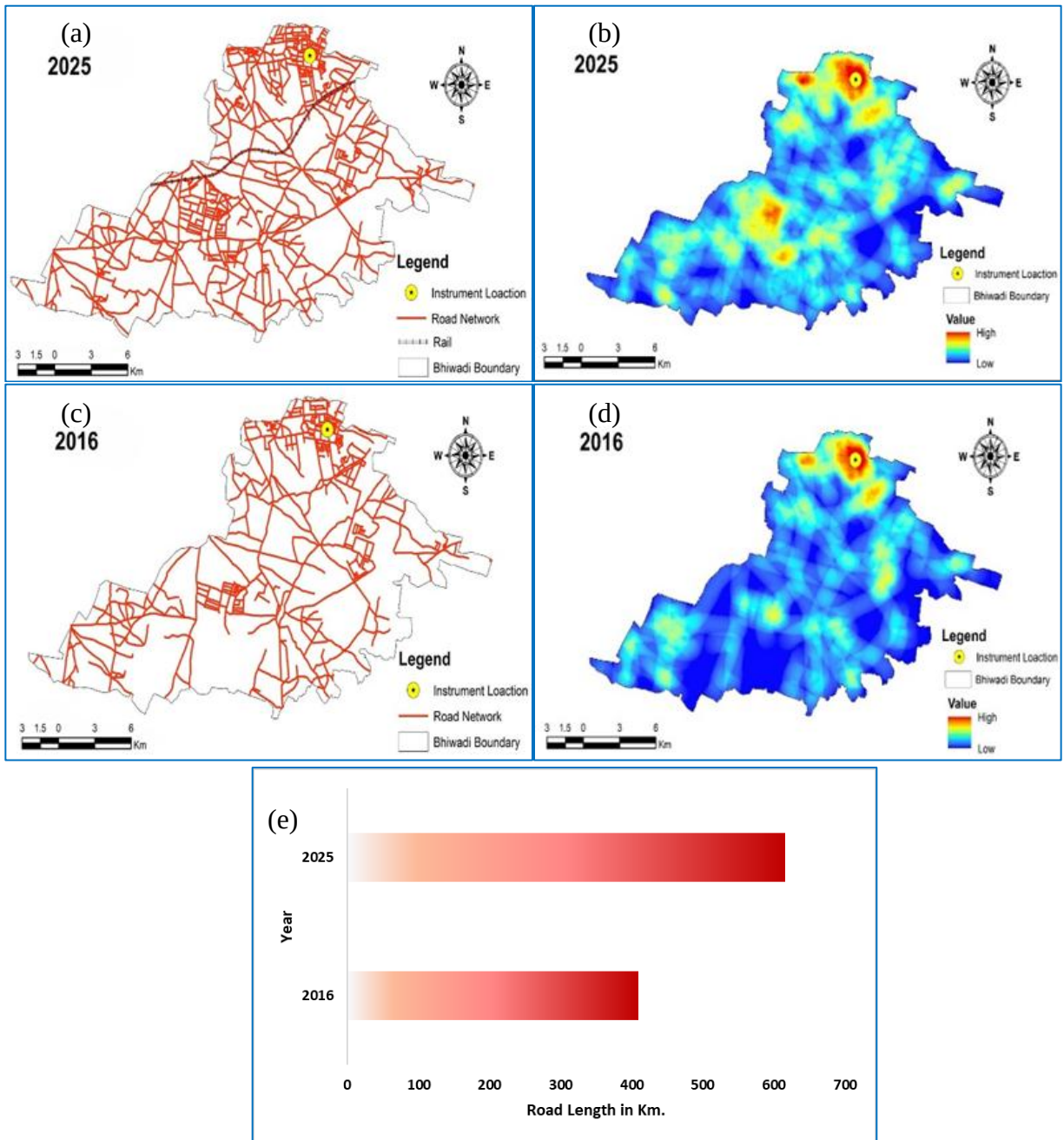


Fig. 7(a-e). (a&c) Road network map of Bhiwadi in 2025 and 2016, (b&d) Road density distribution in Bhiwadi in 2025 and 2016 & (e) Comparative bar chart illustrating total road length in Bhiwadi for 2016 and 2025

Between 2018 and 2019, satellite-derived spectral signatures revealed the emergence of a distinct linear infrastructural feature consistent with a railway line. This infrastructural development appears to have acted as an urban growth pole, catalyzing land conversion along its alignment. By 2020-2025, a network of secondary and tertiary built-up clusters developed along this corridor, particularly in the north-central sector,

producing a characteristic linear-concentrated settlement morphology.

The vegetation area in Bhiwadi shows a consistent declining trend from 173 km² (2016) to 141.7 km² (2025), accompanied by a gradual reduction in NDVI and a steady increase in NDBI, indicating progressive vegetation loss and intensifying built-up development over the decade.

NDVI-derived vegetation cover data reveal a corresponding and inverse trend: a decline from 173.04 km² in 2016 to 141.72 km² in 2025, amounting to a loss of 31.32 km² (18.1%) of vegetated land. The sharpest vegetation loss coincided with phases of high NDBI growth, especially in the north-central industrial estates and adjoining northern periphery (Fig 4 and 5). This inverse relationship reflects a spectrally measurable trade-off between vegetated areas and impervious surfaces (Seto *et al.* 2011) that urban expansion in industrializing regions predominantly occurs at the expense of agricultural and green cover. The spatial comparison of NDBI and NDVI trends thus provides quantitative evidence of landscape homogenization, with natural heterogeneity giving way to built-up monocultures a transformation with direct implications for local microclimate and air quality.

3.2. Land Use/Land Cover Changes (LULC)

The LULC classification outputs, derived from Sentinel-2 imagery processed via unsupervised K-means clustering and refined in ArcMap, capture the multi-class dynamics of Bhiwadi's landscape transformation.

The land use/land cover (LULC) analysis between 2016 and 2025 reveals significant transformations in the study area. The built-up area expanded substantially from 92.96 km² in 2016 to 117.23 km² in 2025, marking an increase of 24.27 km² (26.1%), which is consistent with the NDBI-derived results and highlights rapid urban growth shown in Fig 6. In contrast, vegetation cover experienced the steepest decline, shrinking from 83.65 km² to 48.11 km², indicating a net loss of 35.54 km² (42.5%). Bare land witnessed a dramatic rise, more than doubling from 8.77 km² to 22.92 km² (161%), reflecting increasing construction activities, mining scars, and land awaiting development. Cultivated land showed only a modest reduction, declining from 99.82 km² to 96.95 km², suggesting that peri-urban agriculture continues to persist despite ongoing encroachment pressures. Water bodies, however, exhibited a marginal decline from 0.046 km² to 0.021 km², largely attributable to encroachment and siltation processes. Collectively, these changes underscore the dominance of urban expansion at the cost of natural vegetation and water resources, thereby raising concerns over ecological sustainability and land degradation.

Accuracy evaluation of the classified LULC maps for 2016 and 2025 demonstrates a high level of reliability in the K-means-derived outputs (Table 2). The 2016 map recorded an overall accuracy of 88.66% with a Kappa coefficient of 0.843, indicating almost perfect agreement with reference data. Built-up and cultivated land showed strong classification consistency (PA = 87.04% and 90.00%; UA = 92.16% and 90.00%, respectively).

Vegetation displayed excellent producer accuracy (100%), although some confusion with cultivated areas lowered its user accuracy to 82.22%. Bare land exhibited moderate producer accuracy (66.67%) owing to spectral overlap with dry agricultural surfaces. Water bodies were delineated with 100% accuracy.

Similarly, the 2025 LULC map achieved an overall accuracy of 87.33% and a Kappa value of 0.816, again reflecting strong agreement. Vegetation (PA = 89.66%; UA = 92.86%) and cultivated land (PA = 89.71%; UA = 92.42%) remained the most reliably mapped categories, while built-up areas maintained high accuracy (PA = 86.49%; UA = 82.05%). Bare land continued to show moderate producer accuracy (73.33%), consistent with the spectral confusion associated with construction zones and exposed soil in industrial areas. Water bodies were again mapped with perfect accuracy.

Overall, the high accuracies across both years confirm that the LULC maps are robust and suitable for temporal analysis, supporting the reliability of the subsequent change-detection results and interpretations.

Spatially, the north-central and northern sectors experienced the highest intensity of land conversion, where vegetated and cultivated lands were progressively replaced by industrial, warehousing, and residential complexes. The observed increase in bare land is particularly significant, as it serves as a precursor signal of imminent built-up expansion in subsequent years, a phenomenon also observed in urbanising belts of the Indo-Gangetic Plain (Jat *et al.*, 2017). From an environmental science perspective, this LULC transformation pattern directly influences pollutant dispersion characteristics. Reduced vegetation cover diminishes atmospheric pollutant filtration capacity, while increased impervious surfaces exacerbate dust resuspension and heat island effects, aggravating local air quality degradation.

The annual summary of vegetation area, NDVI and NDBI for Bhiwadi is presented in Table 1. Vegetation cover declines from about 173 km² in 2016 to 141.7 km² in 2025, corresponding to an average loss of ~3.5 km² year⁻¹ over the study period. The mean NDVI remains positive throughout (0.19-0.58), with relatively higher values in 2019-2021, indicating comparatively healthier or denser vegetation during those years. Mean NDBI values are consistently negative, reflecting the dominance of non-built surfaces, but show inter-annual fluctuations with less negative values (i.e. stronger built-up signal) after 2018. A comparison of 2016 and 2025 LULC areas (Table 3) reveals that vegetation decreases by ~35.5 km², while cultivated land (+17.4 km²), bare land (+14.2 km²) and built-up area (+4.0 km²) all increase, confirming

TABLE 1

Annual Vegetation Extent, NDVI, and NDBI Statistics for Bhiwadi (2016-2025)

Year	Vegetation Area (km ²)	Mean NDVI	Mean NDBI
2016	173.0	0.458	-0.234
2017	172.6	0.187	-0.252
2018	151.6	0.312	-0.102
2019	162.3	0.579	-0.266
2020	168.4	0.557	-0.262
2021	165.0	0.540	-0.244
2022	157.0	0.393	-0.189
2023	149.5	0.395	-0.195
2024	154.3	0.368	-0.161
2025	141.7	0.392	-0.191

TABLE 2

Accuracy assessment for LULC classification (2016 and 2025)

LULC Class	PA (%) 2016	UA (%) 2016	PA (%) 2025	UA (%) 2025
Built-up	87.04	92.16	86.49	82.05
Cultivated land	90.00	90.00	89.71	92.42
Bare land	66.67	92.31	73.33	68.75
Vegetation	100.00	82.22	89.66	92.86
Water	100.00	100.00	100.00	100.00
Overall accuracy	88.66%	—	87.33%	—
Kappa statistic	0.843	—	0.816	—

TABLE 3

LULC area change and rate (2016-2025)

Class	Area 2016 (km ²)	Area 2025 (km ²)	Rate of Change (km ² /year)
Built-up	92.96	96.95	0.44
Cultivated land	99.82	117.23	1.93
Bare land	8.77	22.92	1.57
Vegetation	83.65	48.11	-3.95
Water	0.05	0.02	0.00

progressive conversion of vegetated land into agriculture, vacant plots and impervious surfaces. Water bodies remain negligible in area and show no meaningful trend.

3.3. Road Network Expansion and Density Analysis

The road network dataset, extracted from Sentinel-2 SFCC composites through manual digitization and

analyzed using ArcMap's Line Density tool, revealed an expansion from 409.78 km in 2016 to 616.72 km in 2025 a 50.5% increase in total road length shown in Fig 7. This infrastructural growth is not evenly distributed; instead, it exhibits a nodal linear growth pattern, with certain corridors experiencing disproportionately high development. A pivotal infrastructural change occurred in 2018, marked by the construction of a railway line cutting

across the study area. This development functioned as a structural driver for subsequent road proliferation, particularly between 2018-2021, as new arterial and feeder roads branched out to connect industrial hubs, residential colonies, and logistic centres.

Road density maps reveal that northern, central, and parts of eastern Bhiwadi saw the steepest increases in connectivity, with certain grid cells exceeding 5 km of road length per square kilometer by 2025. Such high-density transport grids correlate strongly with regions showing the most intense built-up expansion and vegetation loss, indicating an infrastructure–urbanization feedback loop. From a pollution standpoint, the increase in road density is a critical environmental variable. Enhanced vehicular movement in these dense transport grids increases PM_{2.5} and NO_x emissions, while the replacement of permeable surfaces with asphalt and concrete amplifies dust re-entrainment factors that collectively deteriorate local air quality, as corroborated by CPCB monitoring reports for Bhiwadi’s industrial belt.

3.4. Discussion

The integrated multi-temporal analysis of NDBI, NDVI, LULC, and road network density for 2016-2025 reveals a clear trajectory of urban-industrial intensification in Bhiwadi. This expansion is not simply a function of population growth but is strongly aligned with infrastructural policy frameworks, particularly the Delhi-Mumbai Industrial Corridor (DMIC) and state-level industrial promotion schemes.

3.4.1 Urban Expansion and Vegetation Loss: A Coupled Process

The results confirm a strong inverse correlation between NDBI and NDVI trends. Between 2016 and 2025, the built-up area expanded by 27.65 km² (~30.8%), while vegetation cover declined by 31.32 km² (~18.1%). Spatially, this trade-off was most intense in the north-central industrial cluster and along the newly developed railway corridor. This pattern supports the findings of Seto *et al.* (2011), who demonstrated that industrializing cities in developing nations exhibit a linear, corridor-linked sprawl driven by transportation infrastructure. The spatial concentration of built-up expansion in the north-central sector has environmental consequences beyond surface transformation. Vegetation acts as a natural sink for pollutants through dry deposition and stomatal uptake (Nowak *et al.*, 2014). Its removal in high-emission industrial areas therefore, not only eliminates this sink capacity but also exposes bare soil, increasing dust resuspension a key concern in Bhiwadi, which is ranked

among India’s most polluted cities for PM_{2.5} by CPCB (2023).

3.4.2. LULC Shifts as a Precursor to Pollution Dynamics

The LULC results show a 161% increase in bare land from 2016 to 2025, rising from 8.77 km² to 22.92 km². This rapid expansion of bare soil patches is significant because such surfaces are major contributors to fugitive dust emissions when disturbed by construction activity, heavy vehicle movement, or seasonal winds. Given Bhiwadi’s semi-arid climate, these bare patches can act as persistent dust sources well before they are converted into built-up areas. The reduction in cultivated land (-2.87 km²) and vegetation (-35.54 km²) directly impacts biogenic emission patterns and surface energy balance, contributing to localized warming (urban heat island effect). Warmer surface temperatures can enhance the photochemical formation of ground-level ozone - a pollutant that Bhiwadi’s industrial emissions already predispose the area.

The correlation analysis further supports the observed land-use transitions. Mean NDVI and NDBI exhibit a moderate negative correlation ($r = -0.47$), indicating that years with higher built-up intensity (higher NDBI, less negative) tend to coincide with lower vegetation vigour. The relationship between NDBI and total vegetation area is even stronger ($r = -0.68$), suggesting that expansion of impervious and construction surfaces is spatially associated with the reduction in vegetated land. In contrast, the correlation between NDVI and vegetation area is weakly positive ($r = 0.15$), which may be attributed to the mixed contribution of agricultural fields, plantations and fragmented green patches to the overall NDVI signal. Overall, the combined LULC, NDVI and NDBI statistics demonstrate that Bhiwadi’s recent urban growth and road/industrial expansion are occurring at the expense of vegetated land, with a measurable loss of nearly 4 km² of vegetation per year between 2016 and 2025.

3.4.3 Transport Infrastructure as a Development Catalyst and Pollution Driver

The 50.5% increase in road length and the establishment of a railway line in 2018 serve as a textbook example of infrastructure-led urbanization. The road density analysis highlights how northern, central, and eastern sectors became connectivity hotspots, with densities exceeding 5 km/km² in some grids by 2025. High road density facilitates urban growth by increasing accessibility to industrial plots, but it also introduces persistent mobile source emissions. In Bhiwadi, where a

significant fraction of freight and commuter traffic involves diesel-powered vehicles, this growth in road infrastructure likely translates into higher NO_x and black carbon emissions. These pollutants not only degrade air quality but also contribute to regional atmospheric brown clouds, as reported by Ramachandran *et al.* (2020) for north-western India. Moreover, the correlation between transport expansion zones and areas of vegetation loss suggests a positive feedback loop: new roads encourage land conversion, which in turn drives further road development. This feedback is well-documented in the urban growth literature (Xie *et al.*, 2018) and is evident in the spatial alignment of Bhiwadi's 2018–2025 changes.

3.4.4 Implications for Pollution Mitigation

The spatial overlay of built-up expansion, vegetation loss, and road density highlights critical pollution-vulnerable zones. Specifically, the north-central industrial cluster emerges as a “triple-impact” zone where all three stressors loss of vegetation, increase in built-up area, and high road density coincide. From a mitigation perspective, these zones should be prioritized for:

1. Vegetative buffer creation using pollution-tolerant species such as *Azadirachta indica* and *Cassia siamea*.
2. Dust control measures in bare land hotspots via soil stabilization or temporary cover crops.
3. Emission control through cleaner fuels, stricter vehicular inspection norms, and promotion of electrified freight movement within industrial estates.

The temporal granularity of this study (annual scale) also provides a monitoring framework for urban pollution planning allowing authorities to anticipate pollution surges based on land transformation patterns rather than relying solely on reactive measures.

4. Conclusions

The decade-long multi-sensor, multi-parameter analysis presented in this study reveals a distinct pattern of infrastructure-led and industrially driven urban transformation in Bhiwadi, with significant implications for environmental quality. Between 2016 and 2025, built-up areas expanded by 27.65 km², primarily at the expense of vegetation and cultivated land, resulting in a net loss of 31.32 km² of green cover. This decline in vegetated surfaces has reduced the city's natural capacity for pollution mitigation, particularly in the north-central industrial corridor where industrial activity, high road density, and vegetation loss converge. The sharp 161% increase in bare land highlights the transitional nature of

peri-urban zones, which act as persistent dust sources prior to full urban conversion. Road network expansion, including a 50.5% increase in total length and the establishment of a railway line in 2018, has facilitated urban sprawl while contributing to mobile source emissions. By combining NDVI, NDBI, LULC classification, and transport density mapping, this study demonstrates the value of geospatial techniques in linking land transformation with pollution vulnerability. The findings underscore the urgent need for integrated urban planning that incorporates vegetative buffers, dust suppression measures, and cleaner transport strategies to mitigate the compounding effects of industrial growth on air quality in one of India's most polluted urban-industrial hubs.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

Author statement

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Data Availability

The data used for this work is freely available on European Space Agency (ESA) and Copernicus Programme. Open access Sentinel-2 satellite data used for landuse/land cover (LULC) analysis of the study.

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References

- Abhijith, K. V., Kumar, P., Gallagher, J., McNabola, A., Baldauf, R., Pilla, F., & Pulvirenti, B. 2017, "Air pollution abatement performances of green infrastructure in open road and built-up street canyon environments – A review". *Atmos. Environ.*, 162, 71–86. <https://doi.org/10.1016/j.atmosenv.2017.05.014>
- Badach, J., Dymnicka, M., & Baranowski, A., 2020, "Urban vegetation in air quality management: A review and policy framework". *Sustainability*, 12(3), 1258. <https://doi.org/10.3390/su12031258>
- Bala, R., Yadav, V. P., Kumar, D. N., & Prasad, R., 2024, "Examining the relationship of major air pollutants with land surface parameters and its monthly variation in Indian cities using satellite data". *J. Appl. Remote Sens.*, 35, 101232. <https://doi.org/10.1016/j.rsase.2024.101232>
- Duan, J., Vigevani, I., Corsini, D., Comin, S., Fini, A., & Ferrini, F., 2022, "Methods to quantify particle air-pollution removal by urban vegetation". *Environmental Advances*, 8, 100230; *Atmos. Environ. X*, 21, 100233. <https://doi.org/10.1016/j.aeaoa.2023.100233>
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. 2017, "Google Earth Engine: Planetary-scale geospatial analysis for everyone". *Remote Sens Environ.*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- Jat, M. K., Choudhary, M., & Saxena, A., 2017, "Urban growth assessment and prediction using RS, GIS and SLEUTH model for a heterogeneous urban fringe". *Egypt. J. Remote Sens. Space Sci.*, 10(3), 1–19. <https://doi.org/10.1016/j.ejrs.2017.02.002>
- Janhäll, S. 2015, "Review on urban vegetation and particle air pollution – Deposition and dispersion". *Atmos. Environ.*, 105, 130–137. <https://doi.org/10.1016/j.atmosenv.2015.01.052>
- Lai, R., Oguchi, T., & Zhong, C., 2022, "Evaluating spatiotemporal patterns of post-eruption vegetation recovery at Unzen Volcano, Japan, from Landsat Time Series. *Remote Sensing*, 14(21), 5419. <https://doi.org/10.3390/rs14215419>
- Mandal, S., Rajiva, A., Kloog, I., Menon, J. S., Lane, K. J., Amini, H., ... & Schwartz, J., 2024, "Nationwide estimation of daily ambient PM_{2.5} from 2008 to 2020 at 1 km² in India using an ensemble approach". *PNAS Nexus*, 3(3), pgae088. <https://doi.org/10.1093/pnasnexus/pgae088>
- Mogno, C., Palmer, P. I., Marvin, M. R., Sharma, S., Chen, Y., & Wild, O., 2023, "Road transport impact on PM_{2.5} pollution over Delhi during the post-monsoon season". *Atmos. Environ. X*, 17, 100200. <https://doi.org/10.1016/j.aeaoa.2022.100200>
- Mueller, W., Wilkinson, P., Milner, J., Loh, M., Vardoulakis, S., Petard, Z., ... & Arvind, D. K., 2022, "The relationship between greenspace and personal exposure to PM_{2.5} during walking trips in Delhi, India". *Environ. Pollut.*, 305, 119294. <https://doi.org/10.1016/j.envpol.2022.119294>
- Nasiri, V., Deljouei, A., Moradi, F., Sadeghi, S. M. M., & Borz, S. A., 2022, "Land use and land cover mapping using Sentinel-2, Landsat-8 Satellite Images, and Google Earth Engine: A comparison of two composition methods". *Remote Sens.*, 14(9), 1977. <https://doi.org/10.3390/rs14091977>
- Oke, T. R., 1988, "Street design and urban canopy layer climate". *Energy Build.*, 11(1–3), 103–113. [10.1016/0378-7788\(88\)90026-6](https://doi.org/10.1016/0378-7788(88)90026-6)
- Paradis, E., 2022, "Probabilistic unsupervised classification for large-scale analysis of spectral imaging data". *Int. J. Appl. Earth Obs. Geoinf.*, 107, 102675. <https://doi.org/10.1016/j.jag.2022.102675>
- Pugh, T.A., MacKenzie, A.R., Whyatt, J.D. and Hewitt, C.N., 2012, "Effectiveness of green infrastructure for improvement of air quality in urban street canyons". *Environ. Sci. Technol.*, 46(14), 7692–7699. <https://doi.org/10.1021/es300826w>
- Saha, M., Al Kafy, A., Bakshi, A., Nath, H., Alsulamy, S., Rahaman, Z.A. and Saroar, M., 2024, "The urban air quality nexus: Assessing the interplay of land cover change and air pollution in emerging South Asian cities". *Environ. Pollut.*, 361, 124877. <https://doi.org/10.1016/j.envpol.2024.124877>
- Seto, K. C., Fragkias, M., Güneralp, B., & Reilly, M. K., 2011, "A meta-analysis of global urban land expansion". *PLoS one*, 6(8), e23777. <https://doi.org/10.1371/journal.pone.0023777>
- Singh, J., Gupta, P., Gupta, D., Verma, S., Prakash, D. and Payra, S., 2020, "Fine particulate pollution and ambient air quality: A case study over an urban site in Delhi, India". *J. Earth Syst. Sci.*, 129(1), p.226. <https://doi.org/10.1007/s12040-020-01495-w>
- Singh, V. and Agarwal, A., 2024, "Variation of PM_{2.5} and inhalation dose across transport microenvironments in Delhi". *Transp. Res. D Trans. Environ.*, 127, 104061. <https://doi.org/10.1016/j.trd.2024.104061>
- Singh, V., Singh, S. and Biswal, A., 2021, "Exceedances and trends of particulate matter (PM_{2.5}) in five Indian megacities". *Sci. Total Environ.*, 750, 141461. <https://doi.org/10.1016/j.scitotenv.2020.141461>
- Tucker, C.J., 1979, "Red and photographic infrared linear combinations for monitoring vegetation". *Remote Sens. Environ.*, 8(2), 127–150. [https://doi.org/10.1016/0034-4257\(79\)90013-0](https://doi.org/10.1016/0034-4257(79)90013-0)
- Waqas, M., Nazeer, M., Wong, M.S., Shaolin, W., Hon, L. and Heo, J., 2024, "Impact of urban spatial factors on NO₂ concentration based on different socio-economic restriction scenarios in US cities". *Atm. Environ.*, 316, 120191. <https://doi.org/10.1016/j.atmosenv.2023.120191>
- Wróblewska, K. and Jeong, B.R., 2021, "Effectiveness of plants and green infrastructure utilization in ambient particulate matter removal". *Environ. Sci. Eur.*, 33(1), 110. <https://doi.org/10.1186/s12302-021-00547-2>
- Yao, M., Smith, M. and Peng, C., 2025, "Modelling the effects of vegetation and urban form on air quality in real urban

environments: A systematic review”, Urban For. Urban Green, 128693. <https://doi.org/10.1016/j.ufug.2025.128693>

Zha, Y., Gao, J. and Ni, S., 2003, “Use of normalized difference built-up index in automatically mapping urban areas from TM imagery”, Int. J. Remote Sens, 24(3), 583–594. <https://doi.org/10.1080/01431160304987>

Web / Institutional / Agency Reports

Commission for Air Quality Management. (2024, December 16). *Order invoking revised GRAP actions in Delhi-NCR* [PDF]. <https://caqm.nic.in/WriteReadData/LINKS/f3184d4a-2d7d-4b4c-b03c-77f630cb3554.pdf>

Commission for Air Quality Management. (n.d.). *Orders under the Graded Response Action Plan (GRAP) for Delhi-NCR*. <https://caqm.nic.in/index1.aspx?langid=1&lev=2&lid=4171&lid=4168>

Central Pollution Control Board. (2009). *National Ambient Air Quality Standards (NAAQS) Notification*. Ministry of Environment, Forest and Climate Change.

Central Pollution Control Board. (2019). *Guidelines for measurement of ambient air pollutants*. CPCB.

Copernicus. (n.d.). *Sentinel-2 Data Documentation (MSI bands/resolution)*. <https://documentation.dataspace.copernicus.eu>

European Space Agency. (n.d.). *Sentinel-2: Colour vision for Copernicus*. ESA. https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2

Government of Rajasthan. (2023). *Greater Bhiwadi Master Plan-2031* [PDF]. Urban Housing & Development / CTP.

<https://www.lsg.urban.rajasthan.gov.in/content/dam/raj/udh/organizations/ctp/pdf/1new16march23greater%20bhiwadi%20report%20and%20notifications.pdf>

Rajasthan State Industrial Development and Investment Corporation. (n.d.). *Industrial area information*. RIICO. <https://riico.rajasthan.gov.in>

IQAir. (2024/2025). *Bhiwadi Air Quality Index (AQI) and India air pollution* [Web page]. IQAir. <https://www.iqair.com/us/india/rajasthan/bhiwadi>

IQAir. (n.d.). *Bhiwadi city page — live/archival AQI context*. IQAir.

Copernicus/Sentinel Hub Scripts. (n.d.). *Standard false-colour (NIR-R-G) composite usage guidance*. Sentinel Hub.

Newspaper / Media / Briefs

TERI/NCAP. (2025). “Source apportionment highlights of NCR cities (e.g., Faridabad). *NCAP/TERI briefs*”. *The Times of India*.

The Wire. (2023, March 14). “*India had eighth-worst air pollution in 2022; Bhiwadi’s rank among most polluted*”.

Congalton, R. G., & Green, K. (2019), “*Assessing the accuracy of remotely sensed data: principles and practices*”. CRC press.

Foody, G. M. (2002), “Status of land cover classification accuracy assessment”. *Remote sensing of environment*, 80(1), 185–201.

Stehman, S. V. (1997), “Selecting and interpreting measures of thematic classification accuracy”. *Remote sensing of Environment*, 62(1), 77–89.

ESRI (2023), “*ArcGIS Pro Spatial Analyst Tool Reference*”. Environmental Systems Research Institute.

