

Land Use Land Cover (LULC) Change Detection in Delhi NCT Using Multi-Sensor Satellite Data and Google Earth Engine

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Abstract: *Land Use Land Cover (LULC) change detection is essential for understanding the dynamics of human modified landscapes and for supporting effective land management and urban planning. This study analyses LULC change across the Delhi National Capital Territory over a fifteen-year period, from 2010 to 2025, to assess urban sprawl and its environmental impact in one of India's fastest growing metropolitan regions. Multi temporal Landsat imagery was used as the primary data source, processed on Google Earth Engine, the cloud-based platform that enabled efficient handling and visualisation of large geospatial datasets. Five classes, built up area, agricultural land, vegetation, water, and barren land, were mapped and monitored, and classification accuracy was assessed for both dates. The Normalised Difference Vegetation Index was additionally employed to track vegetation vigour and ecological change. Results reveal a marked expansion of built-up areas alongside a substantial decline in agricultural and vegetated land, driven by peri urban growth along the northwestern and southwestern fringe. NDVI analysis shows rising greenness across the outer belt, reflecting more intensive cultivation on land that remains under crops, a pattern that complements rather than contradicts the measured loss of vegetated area. Combining classification based and an index-based approach provides a robust, scalable framework for LULC monitoring. By revealing where and how urban growth is reshaping the landscape, the study offers a transferable basis for environmental assessment, resource management, and sustainable urban planning in rapidly urbanising regions worldwide.*

Keywords: Urban Sprawl, LULC Change Detection, Google Earth Engine, NDVI, Delhi NCT

1. Introduction

Land Use and Land Cover (LULC) change is one of the most important expressions of environmental transformation and urban development. LULC refers to the physical characteristics of the Earth's surface like vegetation, water bodies, barren land and built-up surfaces, together with the ways in which humans use them. Across the globe, and particularly in developing countries, rapid population growth, industrialisation, construction and economic expansion continue to accelerate the pace at which land is converted from one use to another. Because these conversions influence ecosystems, biodiversity, climate, water resources, agriculture and overall environmental sustainability, the systematic monitoring of LULC dynamics has become a central component of sound environmental management (Talukdar et al., 2020; Agarwal & Kumar, 2024).

The Delhi National Capital Territory (NCT) is among the fastest-growing metropolitan regions in India and has undergone considerable urban expansion over the past two decades. Population growth, in-migration, industrial development and the extension of transportation networks have driven the conversion of agricultural land, vegetation and green space into built-up area (Naikoo et al., 2020; Singh et al., 2022). Recent assessments confirm that this expansion is both rapid and spatially uneven, with the strongest growth occurring along the peri-urban fringe (Nahid et al., 2025). Such processes contribute to habitat fragmentation, intensification of the urban heat island effect, loss of vegetation cover and increased surface runoff (Mohan et al., 2020; Islam et al., 2024), which is why a reliable and repeatable evaluation of these changes is urgently required.

Conventional field-based surveys for monitoring land use change are costly, time-consuming and impractical over large geographic areas. Remote sensing and Geographic Information Systems (GIS) offer an efficient alternative

through repetitive, systematic and spatially continuous observation of the Earth's surface (Mishra et al., 2024; Agarwal et al., 2021; Qin et al., 2021; Panday et al., 2021; Singh et al., 2025; Tripathi et al., 2025). The emergence of cloud-computing platforms such as Google Earth Engine (GEE), coupled with the availability of free satellite imagery, has further improved the ease and efficiency of large-scale temporal analysis (Biswas et al., 2023). Despite these advances, detecting multiple land-cover classes in complex urban environments remains difficult because of the spectral similarity among different urban surfaces, seasonal variability in vegetation cover and differences in the spatial resolution of the available sensors.

A large body of research has demonstrated the value of remote sensing for monitoring LULC in urban and peri-urban settings. Landsat data have become especially popular for long-term monitoring owing to their extensive archive, moderate spatial resolution and free availability. Higher-resolution datasets such as Sentinel-1, Sentinel-2 and PlanetScope have expanded the capacity to identify small-scale land-cover features (Vizzari, 2022). Combining several sensors allows researchers to exploit their complementary spatial, temporal and spectral properties and thereby obtain more accurate information than any single sensor can provide; fusing optical and radar data, for example, has been shown to substantially improve classification accuracy in heterogeneous urban landscapes (Dagne et al., 2023).

Numerous classification approaches have been applied to LULC analysis, including supervised and unsupervised classification, Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees and Random Forest (RF). Among these, the Random Forest classifier has gained wide acceptance because of its ability to handle large, high-dimensional datasets, its resistance to overfitting and its capacity to deliver high accuracy with relatively

straightforward parameterisation (Talukdar et al., 2020; Biswas et al., 2023).

Spectral indices are frequently used to extract thematic information from satellite imagery. The Normalized Difference Vegetation Index (NDVI) is widely applied to assess vegetation condition, biomass and ecological status, while the Normalized Difference Built-up Index (NDBI), Normalized Difference Water Index (NDWI) and Bare Soil Index (BSI) are effective in delineating built-up surfaces, water bodies and bare land respectively. Such indices enhance the separability of land-cover classes and add complementary information to the original spectral bands (Singh et al., 2023; Zhao et al., 2024).

Google Earth Engine has become a particularly useful geospatial tool because it allows petabyte-scale analysis of remotely sensed data without the need for high-performance local computing infrastructure. Its extensive satellite archive, built-in geospatial algorithms and parallel-processing capability have made it a widely adopted platform for LULC studies worldwide, addressing themes such as urban sprawl, deforestation, agricultural monitoring and regional or global environmental change. Nevertheless, relatively few studies have combined multi-sensor satellite imagery, machine-learning classification and vegetation-change detection within a single framework to evaluate the long-term urban development of Delhi NCR.

The present study addresses this gap by developing an integrated approach for analysing LULC change in Delhi NCT over a fifteen-year period using multi-sensor satellite imagery and Google Earth Engine. In contrast to studies that rely on a single data source, this work draws on Landsat, Sentinel-1 and Planet imagery in order to capitalise on the distinct resolution, revisit frequency and spectral characteristics of each sensor. Machine-learning classification is combined with vegetation analysis to map land-use and land-cover change more reliably and to estimate the ecological consequences of urbanisation. Land-cover categories like built-up area, agricultural land, vegetation, water bodies and barren land are classified and mapped, while the NDVI is employed to examine land-cover and ecological change simultaneously. By exploiting the cloud-computing environment of GEE for the rapid visualisation and analysis of large geospatial datasets, the study also demonstrates how the integration of multi-sensor imagery, machine-learning classification and cloud-based geospatial analysis can form a transferable framework for monitoring urban expansion in other rapidly growing cities.

Accordingly, the principal aim of this research is to analyse LULC change in the Delhi National Capital Territory over the past fifteen years, using multi-sensor satellite image analysis within Google Earth Engine, in order to assess urbanisation and its associated environmental effects. To achieve this aim, the study prepares a multi-temporal satellite dataset for the region and integrates multi-sensor imagery for comprehensive analysis; classifies the study area into built-up area, agricultural land, vegetation cover, water bodies and bare land; assesses vegetation status and ecological condition through the NDVI; detects LULC change over the 2010–2025 period; evaluates the spatial extent of urbanisation and its

impact on vegetation and agriculture; and, finally, provides a scientific basis to inform sustainable urban planning and environmental policy for Delhi NCR.

2. Study Area

The study area for this research is the National Capital Territory (NCT) of Delhi, the union territory that contains the national capital and forms the core of the wider Delhi metropolitan region in northern India. The territory covers an area of approximately 1,483 km² and lies between latitudes 28°22' and 28°54' N and longitudes 76°48' and 77°23' E, bordered by the state of Haryana on three sides and by Uttar Pradesh to the east, and is divided administratively into eleven districts. Physiographically, its landscape can be separated into three units: the low-lying alluvial flood plains of the Yamuna River, which traverses the territory from north to south; the rocky Delhi Ridge, a northern extension of the Aravalli range that runs along the south-western margin; and the extensive Gangetic plain that covers most of the remaining area. Elevation ranges from about 180 m to 316 m above mean sea level.

The NCT of Delhi experiences a semi-arid to humid-subtropical climate marked by hot summers, a distinct south-west monsoon season and cool winters. Summer temperatures can exceed 45 °C while winter minima fall close to freezing, and the mean annual rainfall of roughly 600–800 mm is concentrated within the monsoon months of July to September. This strong seasonality in both temperature and vegetation greenness complicates the discrimination of land-cover classes across dates and therefore motivates the multi-sensor, multi-temporal approach adopted in this study (Singh et al., 2023).

The territory was selected because it is among the most densely populated and rapidly transforming urban areas in India, with a 2011 population of about 16.8 million and one of the highest population densities in the country. Decades of population growth, in-migration and infrastructure development have driven the progressive conversion of agricultural land, vegetation and open ground into built-up surfaces, particularly along the urban fringe (Singh et al., 2022; Nahid et al., 2025). These changes have been accompanied by documented environmental pressures, including declining green cover and intensification of the urban heat island effect within the city (Mohan et al., 2020). Because the NCT of Delhi contains a dense built-up core, transitional peri-urban zones, remnant agricultural land, the Yamuna and its associated water bodies, and patches of barren land within a single, well-defined administrative boundary, it offers an ideal setting for a fifteen-year (2010–2025) multi-sensor assessment of land use and land cover change.

3. Data and Methodology

3.1 Data Used

This study focuses on the National Capital Territory (NCT) of Delhi. The boundary was taken from the FAO GAUL 2015 dataset, where the individual district polygons of Delhi were joined together to form one single study-area outline. Only

the NCT was used, not the wider National Capital Region (NCR).

The main data source is satellite imagery from the Landsat programme (Collection 2, Level-2 Surface Reflectance). Two time points were compared: 2010 imagery from Landsat 5; and 2025 imagery from Landsat 8 and Landsat 9 combined. Using only Landsat keeps the data consistent across the 15-year gap. Instead of taking pictures from the whole year, images were selected only from the winter (rabi) crop season, November to March. This is important because farm fields are green and growing in winter; using full-year images would mix these green months with bare, harvested months and make crops wrongly look like empty land. Only images with less than 30% cloud cover were used. For teaching the computer what each land type looks like, the ESA WorldCover 2021 map (10 m resolution) was used as reference. Its categories were regrouped into five simple classes: Built-up, Agriculture, Vegetation, Water, and Barren land. All processing was carried out on the Google Earth Engine (GEE) cloud platform.

3.2 Methodology

Step 1 – Cleaning the images. Clouds and cloud shadows were removed using the quality (QA) band of each image, and the pixel values were rescaled to correct reflectance values. Many cleaned images from the season were then merged into one clear picture using the median (middle value) of each pixel.

Step 2 – Calculating spectral indices. Four indices were calculated from the growing-season image to highlight different surfaces. The Normalized Difference Vegetation Index (NDVI) shows healthy plants, the Normalized Difference Built-up Index (NDBI) shows buildings, the Normalized Difference Water Index (NDWI) shows water, and the Bare Soil Index (BSI) highlights bare ground:

$$NDVI = \frac{NIR - Red}{NIR + Red} \text{ (Equation 1)}$$

$$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR} \text{ (Equation 2)}$$

$$NDWI = \frac{Green - NIR}{Green + NIR} \text{ ((Equation 3)}$$

$$BSI = \frac{(SWIR1 + Red) - (NIR + Blue)}{(SWIR1 + Red) + (NIR + Blue)} \text{ (Equation 4)}$$

Here NIR is the near-infrared band and SWIR1 is a short-wave infrared band. Healthy vegetation reflects a lot of NIR light, so it gives a high NDVI (close to +1), while bare or built surfaces give low values. BSI was added because bare land and built-up areas both have little vegetation and are easily confused; BSI is high over open soil, which helps tell the two apart.

Step 3 – Adding a season-change feature. Crops and natural vegetation are both green in winter, so a single winter image cannot easily separate them. To fix this, a second image from the dry season (April to mid-June) was used to measure NDVI

again after the winter crops are harvested. The NDVI amplitude was then calculated:

$$\begin{aligned} NDVI \text{ amplitude} \\ &= NDVI_{growing} \\ &- NDVI_{dry} \text{ (Equation 5)} \end{aligned}$$

Cropland turns from green (winter) to bare (summer), giving a high amplitude, while trees and grassland stay greener all year, giving a low amplitude. This feature strongly helps separate Agriculture from natural Vegetation.

Step 4 – Collecting training samples. Sample points were chosen from the WorldCover reference map using stratified sampling (an equal number of points per class, about 150 each). At each point, the values of all the bands and indices (including BSI, dry-season NDVI and NDVI amplitude) were read separately from the 2010 image and the 2025 image, so each year is trained on its own data.

Step 5 – Classification. A Random Forest classifier (a machine-learning method that combines 100 decision "trees" and takes a majority vote) was trained to recognise the five classes. A separate classifier was made for each year to avoid errors caused by differences between the old and new satellites. Each pixel of both images was then labelled into one of the five classes.

Step 6 – Checking accuracy. 70% of the sample points were used for training and 30% kept aside for testing. A confusion matrix compared predicted classes with true classes. Two measures were calculated:

$$\begin{aligned} \text{Overall Accuracy} \\ &= \frac{\text{Correctly classified points}}{\text{Total tested points}} \text{ (Equation 6)} \end{aligned}$$

$$Kappa = \frac{P_o - P_e}{1 - P_e} \text{ (Equation 7)}$$

where P_o is the observed agreement and P_e is the agreement expected by chance. Kappa is stricter because it removes lucky guesses. It should be noted that accuracy here was checked against the WorldCover 2021 reference map, not against field surveys. Because the 2010 images are 11 years older than these labels, some real ground changes between 2010 and 2021 lower the measured 2010 accuracy. The results are therefore a fair estimate, but the reference data sets the upper limit of accuracy.

Step 7 – Change detection. The 2010 and 2025 maps were compared to find where each class was gained or lost (for example, new built-up areas). The area of each class (in km²) was calculated for both years, and the NDVI difference (2025 minus 2010) was mapped to show where greenness increased or decreased.

4. Results and Discussion

4.1 LULC Classification and Accuracy Assessment

The classified maps for 2010 and 2025 (Figure 1) show how land cover is arranged across Delhi NCT, sorted into five

classes: built up area, agricultural land, vegetation, water and barren land. In both years the built up class forms a dense, continuous core through central and eastern Delhi and pushes outward along the main arterial corridors that radiate from New Delhi. Agricultural land holds the outer reaches of the territory, tracing a broad arc across the northwest around Narela, Bawana and Alipur and across the southwest near Najafgarh and the Dwarka periphery, where urban growth has yet to take firm hold. Vegetation is more scattered. It appears mostly as a broken band along the Yamuna floodplain in the

east and in patches tied to the Delhi Ridge and the protected forests of the south and southwest. Water is confined almost entirely to the Yamuna and a handful of smaller bodies, while barren land turns up in isolated pockets, most noticeably beside active construction fronts and along the riverbanks. Set next to each other, the two years tell a clear story of expansion. Between 2010 and 2025 the built up class thickens and spreads outward, spilling into land that was previously farmed along the northwestern and southwestern edges, and the agricultural belt shrinks and breaks apart in response.

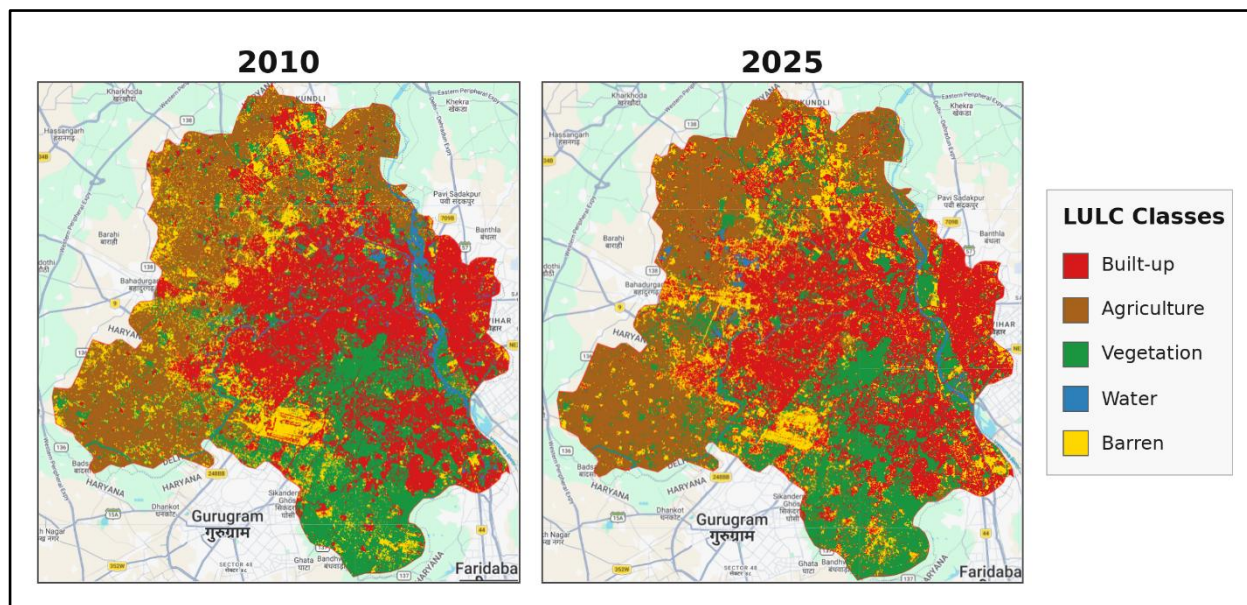


Figure 1: Classified land use and land cover (LULC) maps of Delhi NCT for 2010 and 2025, showing five classes: built-up, agriculture, vegetation, water and barren land.

An accuracy assessment tells us how far the classified map can be trusted, by checking the label the classifier assigned to each location against what the land cover there is actually known to be. This is usually done with a set of reference points whose true class is taken as correct, and the two most common summary measures are overall accuracy, the simple share of points the map got right, and the Kappa coefficient, which adjusts that figure for the agreement you would expect by chance alone. Together they give a sense of how reliable the map is before any conclusions are drawn from it. The accuracy assessment (Table 1) points to moderate agreement for both dates. Overall accuracy rose from roughly 62 percent, with a Kappa of about 0.53, in 2010 to roughly 68 percent, with a Kappa of about 0.60, in 2025. Both values sit within the moderate band commonly used when interpreting Kappa. Part of this gain came from adding NDVI amplitude and the Bare Soil Index (BSI) to the raw spectral bands. These extra features sharpened the boundary between class pairs that are otherwise hard to tell apart from reflectance alone, particularly Agriculture against Vegetation and Barren against Built up.

Table 1: Classification accuracy of the LULC maps for 2010 and 2025, reported as overall accuracy (OA) and the Kappa coefficient.

Classification Year	Overall Accuracy (OA)	Kappa Coefficient
2010	≈ 62%	≈ 0.53
2025	≈ 68%	≈ 0.60

Even with this improvement, some confusion remains in the 2025 result. A share of barren pixels, mostly exposed soil at active construction sites, is still read as built up. This is a familiar problem, since bare soil and sealed surfaces overlap closely in multispectral imagery and are genuinely difficult to separate. One limitation of the assessment itself also deserves mention. Accuracy was checked against the ESA WorldCover 2021 product, which does not match the date of either classification. Because that reference sits much closer in time to 2025 than to 2010, the figure reported for 2010 is probably a cautious underestimate of the real quality of that map. It is better to treat the gap between the classification dates and the reference year as a limit on the accuracy that could ever be recovered here, rather than as a true measure of how the classifier performed in 2010.

4.2 Land Use / Land Cover Change (2010–2025)

Land cover change analysis quantifies how the area of each class expands or contracts over time and reveals the spatial pattern of those transitions, both of which are essential for understanding the pace and direction of urbanisation in a rapidly growing region such as the NCT. Measuring the gain and loss in each class, and locating where conversion is concentrated, makes it possible to identify which land types are being displaced by urban growth and through which transition pathways. Table 2 sets out the area in square kilometres held by each LULC class in 2010 and 2025. Read through the change detection layers, the built up class recorded the largest net gain across the fifteen-year span,

while agricultural land recorded the largest net loss. Vegetation and barren land shifted by comparatively small amounts, and the water class stayed broadly steady, which reflects the fixed course of the Yamuna and the limited change in the extent of surface waterbodies over the study period.

Table 2: Area (km²) of each LULC class in Delhi NCT for 2010 and 2025, with the percentage change between the two dates

LULC Class	Area 2010 (km ²)	Area 2025 (km ²)	Change (%)
Built-up	≈ 600	≈ 785	+30.8
Agriculture	≈ 560	≈ 395	-29.5
Vegetation	≈ 235	≈ 250	+6.4
Water	≈ 35	≈ 34	-2.9
Barren	≈ 53	≈ 19	-64.2

The spatial pattern of new built up development (Figure 2) confirms that growth was far from even across the NCT. The densest cluster of new built up pixels between 2010 and 2025 sits in the outer and peripheral zones, above all the Narela,

Bawana and Alipur belt in the northwest and the Najafgarh and Dwarka periphery in the southwest, together with infill densification inside the already built up core of central Delhi. This matches the peri urban growth trajectory described in earlier work on Delhi, in which the fringe rather than the historic core takes up most of the new construction. The agricultural loss layer (Figure 2) carries a closely overlapping signature. The pixels that moved out of agriculture between 2010 and 2025 gather along the very same northwestern and southwestern fringe zones picked out in the built up expansion map. This tells us that the conversion of cropland into built up use is the leading transition pathway here, rather than farmland drifting into fallow, barren, or some other class that is not urban. Vegetation loss (Figure 2) traces a related but looser pattern. It shows up in small, scattered patches around the edge of the NCT, at Narela, Najafgarh, Dwarka and the Loni and eastern boundary, rather than as one solid block. The suggestion is that tree cover and green patches are being chipped away piece by piece as development fronts push forward, not removed in large clearance events.

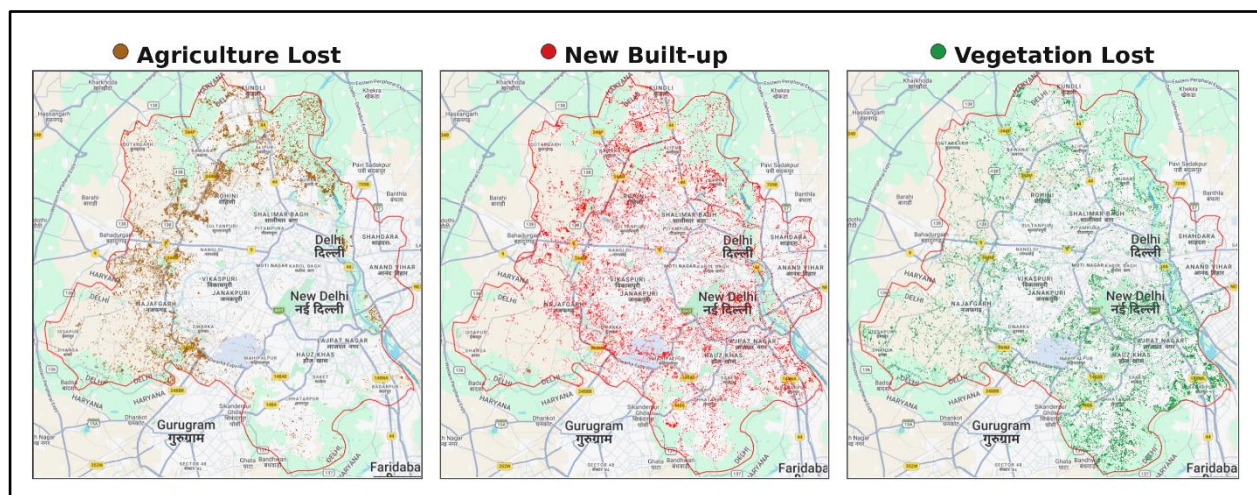


Figure 2: Spatial distribution of land-cover change in Delhi NCT, 2010–2025: (a) agriculture lost, (b) new built-up, and (c) vegetation lost. Each coloured pixel marks a location that transitioned in the corresponding class.

Taken together, these results support a clear account of what is driving the change. Rapid population growth and outward urban expansion in the NCT are turning cropland and open peripheral land into built up surfaces, a pattern well documented across Delhi's wider development history. Even so, it is worth stressing that transition estimates of this kind are only as sound as the classification that underpins them. Given the moderate Kappa values reported in Section 4.1, small changes of a few percent of class area should be read with care, since they may reflect classification noise as much as real conversion on the ground. The large and spatially consistent changes visible in the built-up expansion and agricultural loss layers, however, sit well above that noise threshold and can be read with much greater confidence.

4.3 Vegetation Dynamics (NDVI Analysis)

NDVI captures the photosynthetic vigour of the surface, so rather than reducing the territory to a single average that

would hide as much as it reveals, the analysis looks at how greenness is spread across Delhi NCT and how that pattern shifted between 2010 and 2025. The NDVI maps for the two years (Figure 3) share the same broad spatial contrast. Low values, shown in orange and red, gather over the built up core of central and eastern Delhi, where sealed surfaces and thin vegetation cover push the index down. High values, shown in green, gather over the agricultural fringe in the northwest and southwest and along vegetated corridors such as the Ridge. This overall arrangement holds steady across the fifteen year period, yet the line dividing the low and high NDVI zones does appear to move. By 2025 the orange, low vegetation zone reaches further into the western and southwestern periphery, which fits closely with the built up expansion seen earlier in the change analysis.

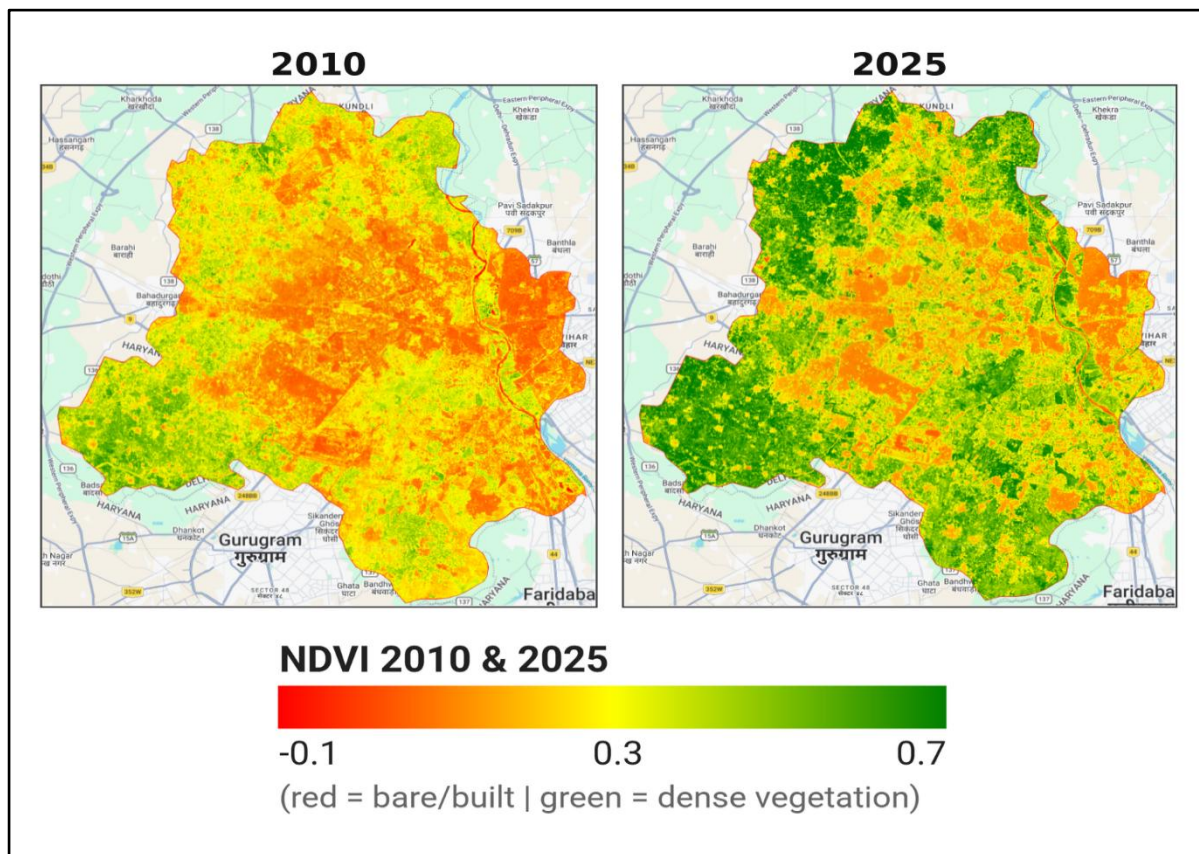


Figure 3: Normalised Difference Vegetation Index (NDVI) for Delhi NCT in 2010 and 2025, ranging from bare or built-up surfaces in red through to dense vegetation in green. The low-NDVI zone widens into the western and southwestern periphery by 2025.

The NDVI change map (Figure 4) shows greenness gain, in green, dominating across most of the outer belt of the NCT, while greenness loss, in red, sits in discrete pockets inside and at the edge of the built up core and along parts of the eastern boundary near Loni and the Yamuna corridor. At first glance this widespread gain across the periphery might seem to contradict the agricultural and vegetation loss reported in the change analysis. That tension is in fact a useful finding rather than an inconsistency. The rising NDVI in the peripheral belt is mostly explained by denser or more vigorous cropland, a move toward more intensive, higher biomass agriculture, wider irrigation, or a shorter fallow cycle, and NDVI, which measures photosynthetic vigour, cannot tell any of this apart from natural or semi natural vegetation. At the same time, the classified vegetation class in these same zones kept contracting wherever agricultural or semi natural land was genuinely turned over to built up use. Put simply, the NDVI trend describes the greenness of land that stays under vegetation or cultivation, while the class area trend describes how much land sits under each cover type. The two are complementary measures rather than directly comparable ones, and the fact that they appear to pull in different directions here is exactly why an index based and a classification based approach were combined in this study.

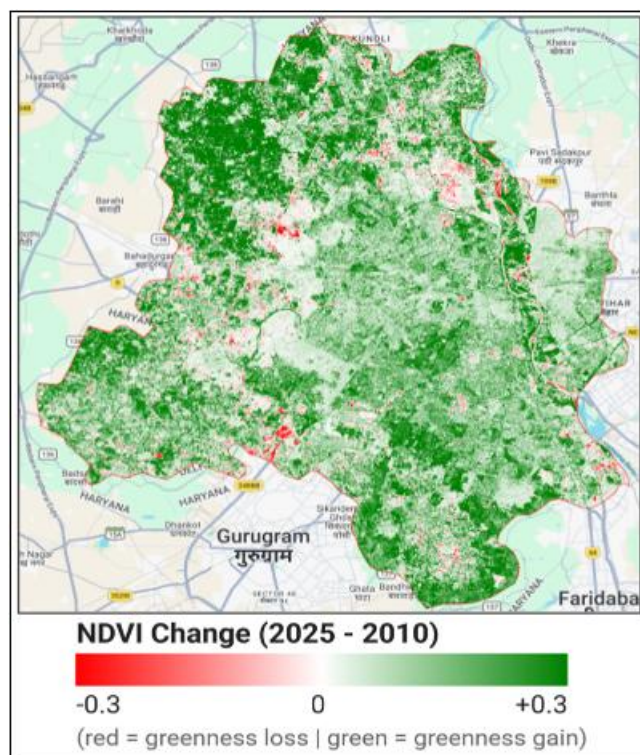


Figure 4: NDVI change map for Delhi NCT (2025 minus 2010), showing greenness gain in green and greenness loss in red. Gains dominate the outer agricultural belt, while losses cluster within and around the built-up core and along the eastern Yamuna corridor.

A further caution applies to how the NDVI trend should be read. Its values respond to changes in monsoon timing and intensity from one year to the next, to how much irrigation is available, and to where the crop calendar happens to fall when the image is captured. A wetter or more favourable growing season in 2025 compared with 2010 could therefore lift greenness on its own, without any real change in the land cover beneath it. Because of this, the continuous NDVI signal is best treated as a less stable guide to long term ecological change than the discrete, class based area changes reported earlier. Those class changes are anchored to the physical conversion of land from one type to another, rather than to the seasonal vigour of the vegetation, and so they carry the more dependable record of what has actually changed on the ground. Read together, the two views give a fuller picture than either could alone: one tracks how vigorously the remaining green surface is growing, the other tracks how much green surface is left.

5. Conclusions

This study set out to map and interpret land use and land cover change across Delhi NCT between 2010 and 2025, and to understand how the territory's vegetation responded to fifteen years of rapid urban growth. By classifying the landscape into five cover types and tracking each of them through time, the analysis established a clear and spatially consistent picture of how the region has transformed. Built up land recorded the largest gain of any class, expanding outward from the dense central core into the northwestern and southwestern periphery, while agricultural land recorded the largest loss over the same period. The change detection layers showed that these two trends are two sides of the same process, with cropland on the urban fringe being converted directly into built up surfaces rather than passing through fallow or barren states. Vegetation loss followed a more scattered pattern around the edges of the territory, consistent with green cover being eroded gradually as development fronts advanced rather than removed in single large clearances.

The main contribution of this work lies in combining a classification based view of land cover with an index based view of vegetation vigour, and in showing why both are needed. Read on its own, the NDVI record suggested widespread greening across the outer belt, which appeared to sit awkwardly beside the measured loss of agricultural and vegetated land. Bringing the two approaches together resolved this apparent tension and turned it into an insight: the periphery is growing greener in intensity, through denser and more vigorous cropland, even as the total area under vegetation and cultivation shrinks. Distinguishing the greenness of the remaining surface from the extent of that surface is a distinction that a single method would have missed, and it is central to interpreting change in a fast urbanising region correctly. Several directions would build naturally on these findings. Extending the time series with additional intermediate years would allow the pace of conversion to be tracked more finely and would reveal whether expansion is accelerating or stabilising. Incorporating higher resolution imagery and additional indices would sharpen the separation of spectrally similar classes and refine the detection of small changes. Finally, linking these land cover trajectories to population,

infrastructure and policy data would help move the analysis from describing where change has occurred toward explaining why, supporting more targeted planning for sustainable growth across the National Capital Territory.

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