A

MAJOR PROJECT-III

REPORT

On

URBAN GREEN SPACE MONITORING

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CANDIDATE’S DECLARATION

We hereby certify that the work on the project entitled, ” **Urban Green Space Monitoring**”, in partial fulfillment of requirements for the award of Degree of **Bachelor of Technology** in School of Engineering and Technology at BML Munjal University, having University Roll No. 220C2030181 and 220C2030065, is an authentic record of our own work carried out during a period from January 2025 to May 2025 under the supervision of Dr Kiran Khatter.

Piyush Garg

Divyanshu Bansal

SUPERVISOR’S DECLARATION

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Faculty Supervisor Name: Dr Kiran Khatter

Signature:

ABSTRACT

The 21st century has witnessed incredible urban growth worldwide, completely altering natural landscapes and systems for ecology. Using the latest satellite imagery and machine learning approaches, our work shows the breathtaking transformation of Gurgaon within the years 2015-2023. Based on a thorough analysis of pre-monsoon satellite information on Google Earth Engine in visible light, infrared and shortwave infrared bands, we realized the cumulative transformation of natural landscapes into built outline/considerations.

Using wide geographically dispersed, field validated data, we adopted the basis for building a strict classification system that clearly defines four essential land classes: Urban areas , vegetations, Water bodies, and Barren land. According to the analysis presented, there are sharp increases in built-up areas at the expense of original vegetation and previously undeveloped hands of land; the high level of regional infrastructure construction is also emphasized.

Remote sensing technologies are demonstrated to be useful in observing urban development in this study and the findings on this regard fulfill critical information towards sustainable planning for rapidly developing cities such as the Gurgaon. Such observations are in line with a larger urbanization process in developing countries and highlight the importance of the combination of growth strategies based on environmental protection with the growth process.

ACKNOWLEDGMENT

I am highly grateful to **Dr. Kiran Khatter**, BML Munjal University, Gurugram, for providing supervision to carry out the seminar/case study from January-May 2025.

Dr. Kiran Khatter has provided great help in carrying out my work and is acknowledged with reverential thanks. Without wise counsel and able guidance, it would have been impossible to complete the training in this manner.

I would like to express thanks profusely to thank **Dr. Kiran Khatter**, for stimulating me from time to time. I would also like to thank the entire team at BML Munjal University. I would also thank my friends who devoted their valuable time and helped me in all possible ways toward successful completion.

(Piyush Garg)

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INTRODUCTION

Overview

Urbanization refers to a shift in life styles, where people move from rural areas to the urban areas, accompanied with increased spatiality of urban areas and infrastructure. The urbanization that is currently in progress is entirely changing the environmental, economic, and social scenarios around the globe at stupendous pace and scale.

By 2025, approximately 58% of the world's population, or 4.8 billion people, live in cities (<100,000 total population), and this number is expected to increase to 62% by 2035. Currently, the world has 37 megacities and this number is estimated to rise to 48 as at 2035. Tokyo, with 37.0 million, Delhi with 34.7 million and Shanghai with 30.5 million are the major urban agglomerations in the year 2025.

The most urban development is found in Northern America, Latin America and the Caribbean, and Europe with Africa still predominantly rural – only 43% are found in urban areas. Burundi leads between the years of 2020-2025 with 5.43% next is Uganda with 5.41% while the third major leading cities for urbanization acceleration is Syria with 5.38%. In the next 30 years, India, China, and Nigeria combined will account for 35% of the world's urban expansion from 2018 to 2050.

The major challenges of rapid urban change are evident in some critical areas. Wrong urban growth accounts for habitat clearance and fragmentation of natural habitat especially in emerging urban regions resulting to loss of biodiversity. Higher numbers of vehicular traffic and industries increase air pollution due to water contamination by urban water bodies and eutrophication. This is a direct contributor to the intensified urban heat-island effect in Gurgaon that reduced vegetation by 41 % between 2015 and 2023. In addition, the increased burning of carbon in urban areas contributes significantly in enhancing climate change.

The spurt in rate of urban growth often leads to housing crisis, which leads to the accelerated growth of slums, affecting one third of urban population. Traffic gridlock reduces productivity and quality of life as a whole thereby increasing the divide between rich and poor urban locations. In cities in regions experiencing a rapid urbanization, crime has skyrocketed in several regions; some report rates exceeding 100 homicides per 100,000 inhabitants. Lifesaving improvements in population require significant strain on important public services such as health, education, and water amenities.

Existing System

In a previous studies, the most common remote sensing data and classification technique utilization strategy to examine urban change has been the use of combined methods. Random Forest (RF) excels among the family of machine learning algorithms with accuracy of 94% on classifying samples of urban land cover through the construction of large numbers of decision trees from several random subsets of the data that are learned. Support Vector Machine (SVM) was at 87% accuracy in land use classification but Classification and Regression Trees (CART) achieved 91% but struggled to describe spatial diversity. Maximum Likelihood (ML) techniques started with 82% accuracy, but their level has dramatically diminished since then and, by 2020, they only managed 66%. With the use of a deep learning approach Convolutional Neural Networks (CNNs) allow for automatic feature extraction of hierarchical form, thus creating flexibility for distinguishing objects that are observed with different color signatures.

In the area of urban growth prediction, almost a half of the studies reviewed use Cellular Automata (CA), with a potential to model changes within reside ecosystems. Other methodologies include: Agent-Based Models (which model individual household behavior in urban spaces); logistic regression (in estimating urban rates although are weak with long-term projections); and Shannon's entropy tool for measuring urban spatial distribution patterns.

Although current practices have been able to deliver important developments, they are still constrained by important issues. Most of the algorithms ignore the effect of spatial-autocorrelation and heterogeneity, as only six of the studied works accounted for both in their models. Adopting standard rules in the decision trees and CA models can mask local variations in growth and development by homogenizing heterogeneous urban environments. Although certain algorithms work well regarding the accuracy, the results obtained do not vary geographically evenly, thus creating areasstart of uncertainty in analysis. Overly complex decision trees traditionally make algorithms fail to generalize well in urban situations. Some preceding research has relied on a small number of sets of data, drawing wide, detailed categorizations that are most distant from the fast-changing and diverse landscapes of developing parts with concentrated informal settlements and mixed land use.

User Requirement Analysis

Accurate land-use change assessment, as caused by urbanization, is an integral part of effective urban governance and planning. Conventional methods such as census data often leave out the level of spatial detail needed for monitoring level changes across neighborhoods, making it ineffective for particular interventions. There is an increasing demand on side of urban planners for detailed updated maps that would allow monitoring encroachment on ecologically sensitive areas, such as wetlands, forests and fields. Policy makers resort to evidence-based understanding to fashion rules and regulations which can promote economic growth while mitigating environmental risks, especially in areas that experience rapid urban spreading threatening to destabilize the ecosystem. Established and replicable processes are required for the researchers in this domain to be able to conduct consistent city-to-city analysis and find out wider trends in urban growth on a global scale. The crucial point is one's sensitivity to the first signs of environmental deterioration – vegetation loss, increase in impervious surfaces, and changes in the watersheds, so that authorities come to the rescue and prevent irreversible ecological damage immediately. The desperate demands for such capacities underline the importance of implementing complex but easy-to-use solutions that integrate multi-temporal satellite observations, AI, and simple-to-use software to both work urban-planners and community-detections to study urban evolution together.

Feasibility Study

To compensate for these drawbacks, our study introduces a set of imaginative approaches and advanced methods. The use of eight spectral bands (Blue, Green, Red, NIR, SWIR1, NDVI, NDBI, NDWI) in our multi-band integration allows us to identify subtle land-use changes that are missed by traditional RGB or low-band techniques. This meticulous spectral approach allows for detecting the attested urban changes of preliminary building construction, incomplete green space removal and hybrid procedures in land-use that could be missed under conventional practices.

We have outperformed the traditional approaches to deep learning optimization by complementing the delicate fine-tuning maneuvers with the polynomial learning rate decay. This is a flexible learning process that allows the model to discover fine urban details, thus reducing misclassifications, in ambiguous transition regions such as peri-urban neighborhoods or informal settlements. We have shaped the architecture of the model in order to make room for the analysis of the diverse and labyrinthine cities more common in the truly growing cities. Equanimity between the emphasis on a large dataset and the election of class samples that ideally optimize within-class divergences and reduce between-class separations is the foundation of our approach. To that end, by carefully compiling the dataset, we were able to attain constant accuracy for a broad range of urban landscapes from the centres of Business districts, spreading suburbs to industrial areas. In order to address these spatial autocorrelation problems, our training method has geographically diverse samples from every category of land use.

Our approach is supported by gathering an extensive training dataset containing class samples with high intra-class diversity and low inter-class differences. Attempting to balance intra-class variances and inter-class similarities in the training dataset, our effort generates model performance that is robust to the diversity of urban landscapes from city centres to new developing residential and industrial urban areas. To handle spatial autocorrelation, the technique uses geographically spread training samples within each category of land use.

In order to facilitate reproducibility and dissemination, we have provided freely accessible open source python scripts with which users can apply our methodologies to regions that undergo similar urban expansion. With these tools, professionals in academia, urban planning and policy can monitor urban transformation into advanced methods using remote sensing and machine learning techniques or not. The modular structure of our workflow allows for custom modulations for regional patterns of growth, spectral properties and data sources.

By capitalizing on these developments, our work builds a powerful analysis tool for Gurgaon's urban growth with uncomparable accuracy and detail, and contributes essential facts required for responsible and environment friendly urban planning and environmental governance in one the most dynamic urban environments in India.

LITERATURE REVIEW

Recent studies on urbanization in Indian cities have predominantly utilized remote sensing (RS) and geographic information systems (GIS) methodologies to quantify land use/land cover (LULC) changes with increasing precision. In Pune, Kadam & Lokhande (2021) and IJFANS (2022) employed Landsat-5/TM and Landsat-8 imagery, applying supervised classification techniques within Google Earth Engine and ArcGIS platforms. These studies measured urban transformation through key metrics including the Normalized Difference Built-up Index (NDBI), vegetation indices (NDVI), and water body assessments. Their findings revealed a substantial increase in Pune's built-up area from 54.03% in 2001 to 63.84% by 2020, representing a 9.81% growth primarily attributed to the expansion of the information technology sector and consequent migration patterns.

Similar methodological rigor was evident in Chakraborty & Singh's (2023) study of Silchar, which analyzed Landsat data spanning 2014–2023. Their approach combined maximum likelihood classification with the Analytical Hierarchy Process (AHP) to evaluate urban expansion. The results documented a dramatic 26% surge in built-up area within this smaller city, with agricultural lands experiencing a significant loss of 23.13 km^2 to accelerating urban sprawl.

Pune's urbanization exhibits distinct spatial trends, with growth concentrated around information technology hubs such as Hinjawadi and Kharadi, as well as along major transportation corridors like the Pune-Mumbai Expressway. Interestingly, despite the intense urbanization, vegetation coverage in Pune increased marginally by 6.01%, attributed to citizen-led environmental initiatives such as the Taljai Hill restoration project. The primary drivers of Pune's expansion include economic factors, particularly IT sector growth and industrial park development, coupled with demographic pressures from both natural population growth (approximately 2.5% annually) and substantial in-migration.

In contrast, Silchar's urbanization has followed a more unplanned trajectory, with expansion occurring predominantly into agricultural and barren lands. This pattern stems from significant population influx combined with inadequate zoning policies and urban planning frameworks. Unlike Pune's modest gains in vegetation, Silchar has experienced vegetation decline due to unregulated encroachment. The drivers behind Silchar's growth differ somewhat from Pune's, with economic factors centered around agro-processing industries, particularly tea and rice production, while governance gaps, especially weak enforcement of urban planning regulations, have facilitated unstructured development.

The environmental impacts of urbanization in Pune present a mixed picture. On the positive side, the city has successfully maintained managed green spaces, particularly in cantonment areas. However, concerning negative effects include the shrinking of water bodies from 1.09% to 0.93% between 2001 and 2021, raising significant concerns about groundwater depletion and long-term water security for the growing urban population.

Silchar faces more severe environmental challenges, with the conversion of 23.13 km^2 of agricultural land to urban use between 2014 and 2023 threatening local food security. Public surveys in Silchar have highlighted additional infrastructure strains, particularly inadequate waste management systems and transportation networks that have failed to keep pace with rapid urbanization. These findings underscore the need for more sustainable urban planning approaches that balance development needs with environmental conservation and infrastructure capacity.

Comparison

Aspect	Pune (Maharashtra)	Silchar (Assam)
Growth Rate	Built-up area increased by **9.81% (2001–2020)** [Kadam & Lokhande, 2021]	Built-up area surged by **26% (2014–2023)** [Choudhury, 2019]
Primary Drivers	IT sector expansion (Hinjawadi, Kharadi) Migration from rural areas	Agro-processing industries (tea, rice) Rural-to-urban migration
Governance	Revised **Comprehensive Development Plan (2041)** guiding expansion	Limited enforcement of zoning laws; unplanned sprawl into wetlands and farmland
Infrastructure	Managed growth with IT corridors and public transit (Metro, BRTS)	Overburdened roads, inadequate waste management, and water supply shortages
Environmental Impact	Vegetation increased marginally (6.01%) due to citizen initiatives Water bodies declined by 0.16%	**23.13 km² agricultural land lost** (2014–2023) Encroachment into wetlands (Barak River basin)
Socioeconomic Factors	High-skilled migration Rising property prices displacing low-income groups	**Slums** house ~300 families with no basic amenities
Historical Context	Post-2000 IT boom transformed rural hinterlands into tech hubs	Colonial-era urbanization (1882–1913) with British administrative expansion
Educational Role	Proximity to institutions like **IIT-Pune** fuels skilled labor demand	**NIT Silchar (1967)** and **Assam University (1994)** drive student migration

Study Area

Gurgaon is one of the major satellite cities of Delhi and forms a significant part of the National Capital Region (NCR). It has emerged as a leading financial and technology hub of India. The total study area of Gurgaon district is approximately 1,460 km^2. The district includes Gurugram Municipal Corporation and surrounding areas.

Figure 1: Geographical area of Gurgaon District, Source: Google Map

Gurgaon district is situated in the semi-arid plains of northern India, forming part of the Indo-Gangetic alluvial plains. The topography of Gurgaon is predominantly flat with a gentle slope from south to north. The elevation ranges approximately between 220-320 meters above mean sea level, with the Aravalli Hills forming the eastern boundary of the district.

The Najafgarh drain (also known as Sahibi River) is the main water channel flowing through the district. While there are no major perennial rivers in Gurgaon, several seasonal streams and water bodies dot the landscape, particularly during the monsoon season.

Objectives

- To quantify and analyze urban expansion patterns in Gurgaon using multi-temporal satellite imagery from 2015, 2020, and 2023.
- To detect changes in green space distribution and density over the 8-year period (2015-2023).
- To perform comprehensive Land Use Land Cover (LULC) classification of the study area.
- To conduct change detection analysis identifying key land use transitions.

Geospatial Dataset

When we set out to conduct our study, we knew we needed reliable, high-quality satellite imagery. Fortunately, two resources were available which were the Landsat program, a collaborative effort between NASA and the US Geological Survey, and the Sentinel mission from the European Union's Copernicus Programme.

Launched on February 11, 2013, Landsat 8 continues a remarkable legacy of Earth observation that stretches back to 1972. What makes this satellite so impressive is its two primary instruments: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). For our research, we focused on the multispectral bands with a 30-meter spatial resolution – detailed enough to capture meaningful land use changes. The satellite's orbit is a marvel of engineering. Flying at an altitude of 705 kilometres in a near-polar, sun-synchronous path, Landsat 8 captures images of the entire Earth every 16 days. Each image covers a whopping 185-kilometer swath, and the satellite manages to collect around 700 scenes daily. This is a significant leap forward from previous Landsat missions.

We specifically used Collection 1, Tier 1 data, which meets rigorous geometric and radiometric quality standards. The data was processed to surface reflectance level, meaning it's been atmospherically corrected to provide the most accurate representation of Earth's surface.

For our more recent analysis covering 2020 and 2023, we turned to the European Space Agency's Sentinel-2 mission. This innovative system consists of twin satellites (Sentinel-2A and Sentinel-2B) positioned 180 degrees apart in the same orbit – a clever configuration that maximizes coverage.

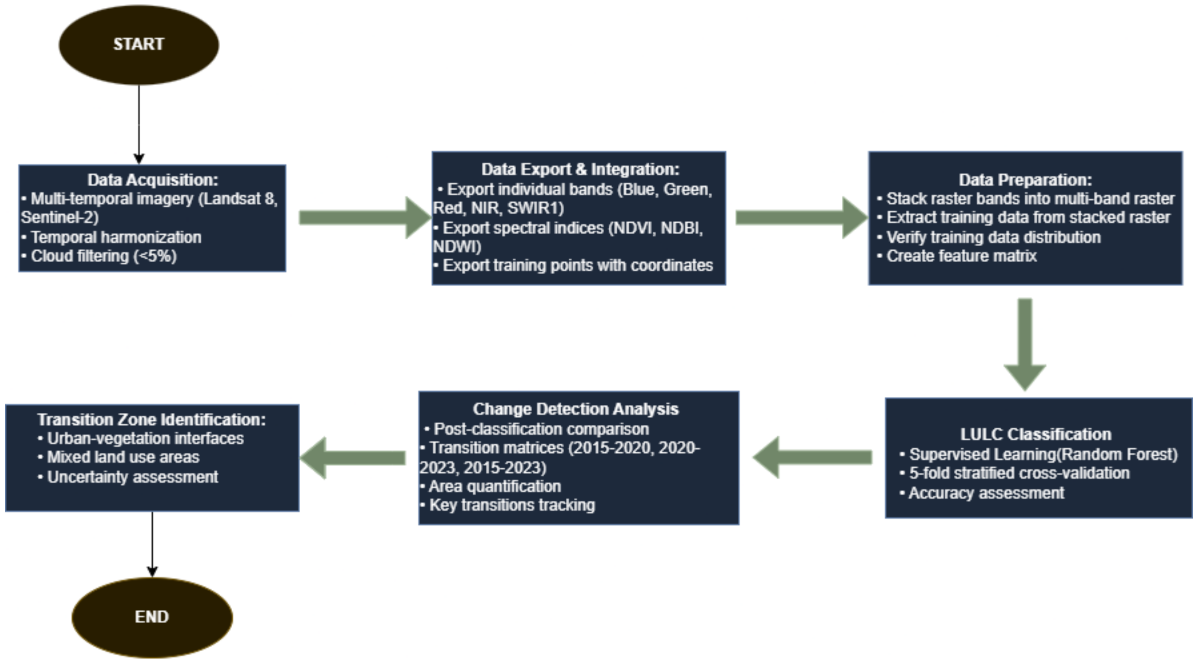
The Multi-Spectral Instrument (MSI) onboard these satellites is truly impressive, offering 13 spectral bands that span from visible to shortwave infrared wavelengths. What sets Sentinel-2 apart is its superior spatial resolution: 10 meters for key visible and near-infrared bands, with additional bands at 20m and 60m resolution. Operating at 786 kilometres altitude, these satellites provide a comprehensive view of land surfaces from 56 degrees south to 84 degrees north. The twin-satellite setup allows for an incredible 5-day revisit cycle, which is a significant improvement over previous satellite systems.

We utilized the harmonized surface reflectance products, which provide analysis-ready data perfect for time-series monitoring and change detection. The data is processed using the Sen2Cor atmospheric correction algorithm, ensuring we have the most accurate bottom-of-atmosphere reflectance values.

The combination of Landsat 8 (30m resolution) for 2015 and Sentinel-2 (10m resolution) for 2020 and 2023 provides an optimal balance between historical coverage and improved spatial detail for recent periods, enhancing our ability to detect and analyze changes across the study timeframe.

METHODOLOGY

This study follows a structured, multi-phase methodology to analyze land use and land cover (LULC) changes in Gurgaon over the years 2015, 2020, and 2023. The methodology integrates satellite imagery processing, machine learning classification, spatial change detection, and ecological analysis. The entire workflow is executed using Python and Google Earth Engine (GEE), incorporating spatial libraries such as Rasterio, Scikit-learn, and Seaborn for statistical validation and visualization.



1. Data Acquisition

We utilized pre-monsoon (March) imagery from Landsat 8 (2015) and Sentinel-2 (2020, 2023), selected for minimal cloud cover (<5%) and processed as surface reflectance products. Images were standardized by clipping to administrative boundaries and reprojecting to EPSG:4326, ensuring reliable comparison of vegetation and built-up indices across the study period.

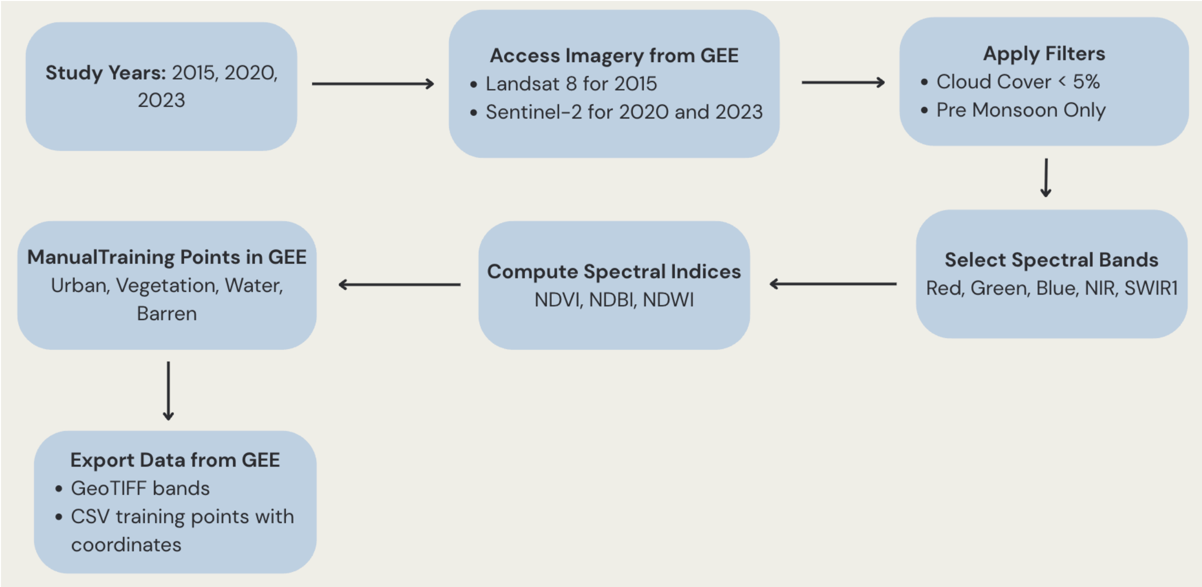


Figure 2 : Data Preparation

2. Band Selection and Index Computation

Each satellite image was decomposed into individual spectral bands required for feature construction

Landsat 8: Blue (B2), Green (B3), Red (B4), NIR (B5), SWIR1 (B6)

Sentinel-2: Blue (B2), Green (B3), Red (B4), NIR (B8), SWIR1 (B11)

From these bands, three key spectral indices were computed:

NDVI (Normalized Difference Vegetation Index):

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}}$$

NDBI (Normalized Difference Built-up Index):

$$\mathrm{NDBI} = \frac{\mathrm{SWIR1} - \mathrm{NIR}}{\mathrm{SWIR1} + \mathrm{NIR}}$$

Due to differing spatial resolutions of Sentinel-2 bands (10m for NIR, 20m for SWIR1), resampling was performed to align the spatial resolution using bilinear interpolation via Rasterio. All computed indices were normalized to a [0, 1] range to ensure scale invariance across years and sensors.

3. Feature Stack Construction and Training Data Extraction

A stacked raster was created for each year, consisting of

Spectral bands: Blue, Green, Red, NIR, SWIR1

Spectral indices: NDVI, NDBI, NDWI

Training points representing four LULC classes—Urban, Vegetation, Water, and Barren—were manually digitized using Google Earth Engine and exported as CSV files. Each point's spectral values were extracted from the stacked raster to form the final **feature matrix (X)** and corresponding **label vector (y)**.

Data quality was assessed using visualizations of class distributions and boxplots of features per class. Invalid or NaN-valued points were discarded.

4. Supervised Classification with Stratified Cross-Validation

A **Random Forest (RF)** classifier was selected for its robustness and ability to handle high-dimensional data. For each year, the following classification strategy was applied **Stratified 5-Fold Cross-Validation** to ensure balanced representation of all LULC classes. Class weights were applied to mitigate class imbalance. Hyperparameters included 100 estimators, max depth of 10, and 'sqrt' feature selection.

Each fold's performance was assessed using **Accuracy**, **Cohen's Kappa Score**, **Confusion Matrix** and **ROC-AUC curves.**

Additionally, **Out-of-Bag (OOB) error** was computed as a generalization estimate. Final models were retrained on the full dataset and saved for future prediction.

5. Full Scene Classification

Using the trained models, pixel-wise classification was performed on the entire stacked raster for each year. Classification was executed in batches to manage memory usage efficiently. The output was a thematic map with each pixel labeled as Urban (Red), Vegetation (Green), Water (Blue), Barren (Yellow). These classified rasters formed the basis for spatio-temporal change analysis.

6. Change Detection and Transition Analysis

To assess land use transitions between time periods (2015–2020, 2020–2023, and 2015–2023), classified rasters were aligned using **nearest-neighbor resampling**. A **transition matrix** was computed for each time pair, capturing pixel-wise conversions between LULC classes.

- Pixel-wise count of transitions
- Area calculation using pixel resolution (30m for Landsat, 10m for Sentinel)

$$\text{Area (km}^2) = N \times \left(\frac{\text{Resolution}^2}{1,000,000} \right)$$

- Percentage change across classes
- Urban expansion quantified by Vegetation-to-Urban transitions

7. Transition Zone Identification

This final phase employed two complementary methods to identify and characterize urban-green ambiguity zones:

Urban-vegetation Interface Analysis

This approach examined the boundaries between urban and vegetated areas, identifying zones of mixed land use. A buffer analysis was performed around urban-vegetation edges to delineate potential transition zones.

Mixed Land Use Assessment

Truth-Indeterminacy-Falsity (T-I-F) Analysis: This method quantified spectral ambiguity by analyzing the relationship between normalized NDBI (urban likelihood) and normalized NDVI (vegetation likelihood). Indeterminacy was calculated as $I(x) = 1 - |T(x) - F(x)|$, with high values indicating pixels with mixed urban-vegetation characteristics.

- **T(x)** = Urban likelihood = normalized NDBI
- **F(x)** = Vegetation likelihood = normalized NDVI
- **I(x)** = Ambiguity score = $1-|T(x)-F(x)F(x)|$

Texture-based Spatial Analysis: This approach assessed spatial heterogeneity using edge detection (Sobel filters) and local diversity indices (Shannon entropy) within 7×7 pixel moving windows. Areas with high edge density and class diversity were identified as ambiguous zones.

The integration of these methods provided a comprehensive assessment of peri-urban complexity, identifying areas that require special consideration in urban planning. Zones flagged by both methods were prioritized as critical transition areas, representing the advancing urban frontier where policy interventions are most needed.

8. Visualization and Interpretation

Classified LULC maps (2015, 2020, 2023), RGB composites with classification overlays, Transition matrices and heatmaps, Area bar charts and urban expansion line graphs and Fragmentation trends and patch visualizations were done. These collectively enabled interpretation of urban expansion dynamics and their ecological implications.

RESULTS

Using Stratified k-fold validation we have generated the LULC classified maps for 2015 ,2020 and 2023. We have used 80% samples for training and 20% samples for testing. We have achieved training accuracy of 97% and overall accuracy of 94%. We have achieved a validation kappa of 87%, indicated by Cohen's Kappa coefficient. It is to be noted that the kappa coefficient of more than 0.8 or 80% indicates a very good strength of agreement. We also calculated AUC (area under curve) which was 0.98 or 98% which represents best results.

	2015			2020			2023		
	Total	Train (80%)	Test (20%)	Total	Train (80%)	Test (20%)	Total	Train (80%)	Test (20%)
Urban	216	173	43	330	264	66	453	362	91
Vegetation	308	247	61	540	432	108	367	293	74
Water	226	180	46	161	129	32	166	133	33
Barren	74	59	15	67	53	14	85	68	17
Overall	824	659	165	1098	878	220	1071	856	215

Table 1 : Samples

Year	Training Accuracy	Testing Accuracy	Overall Accuracy	Cohen's Kappa	Average AUC
2015	0.970874	0.905329	0.9381015	0.86719	0.983927
2020	0.976321	0.917136	0.9467285	0.869655	0.982589
2023	0.96732	0.91594	0.94163	0.875594	0.985532

Table 2 : Validation results

The Confusion Matrix is a performance measurement for evaluating the classification accuracy of multiple classes. The diagonal of a confusion matrix represents the number of instances that the predicted class was correctly classified as an actual class.

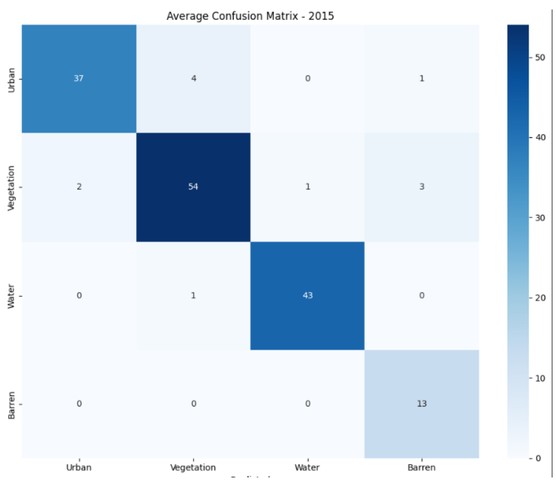


Figure 3 : Confusion Matrix for 2015 year

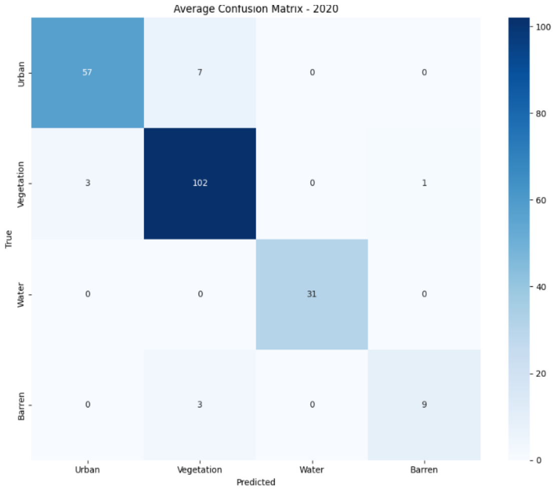


Figure 4 : Confusion Matrix for 2020 year

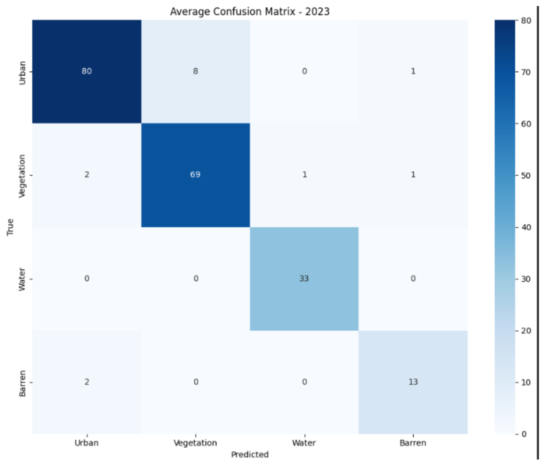
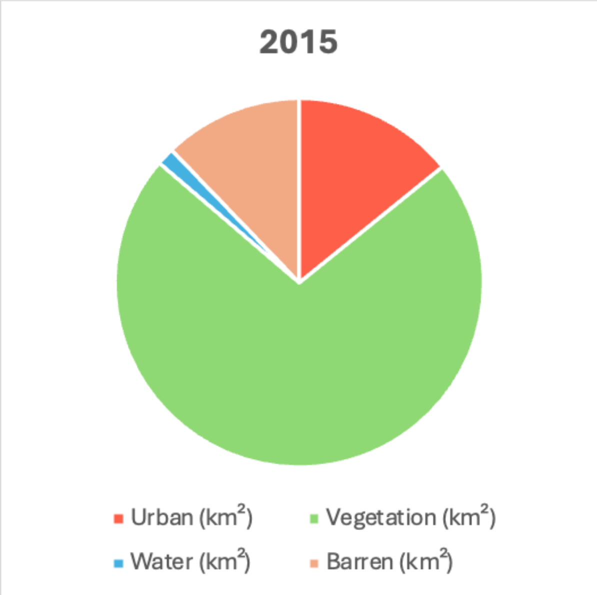


Figure 5 : Confusion Matrix for 2023 year

The highest rate of changes is observed in the urban area class. The urban landscape underwent significant transformation from 2015 to 2023, with the urban area expanding by 40%. Despite this substantial urban growth, vegetation showed resilience with a 3.6% net increase, though recent trends indicate some decline. Water bodies faced considerable pressure, decreasing by 26% over the eight-year period. Perhaps most dramatically, barren land areas diminished by 66%, likely converted to urban development or rehabilitation efforts, representing a major shift in land use patterns across the region.



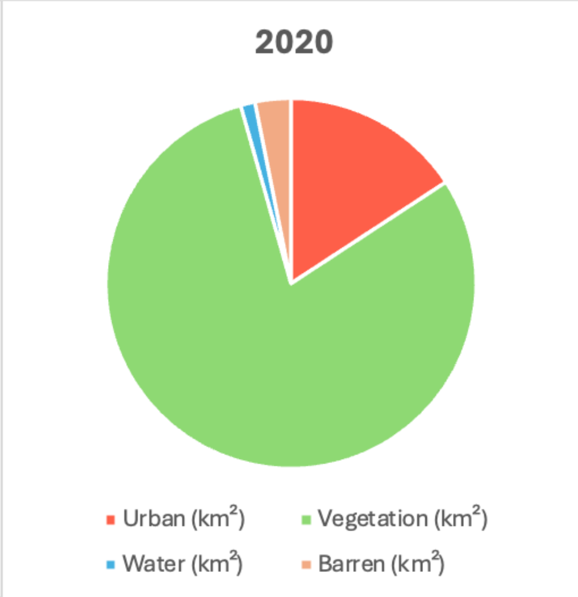


Figure 6 : Land Use Statistics for Pune for 2015 and 2020

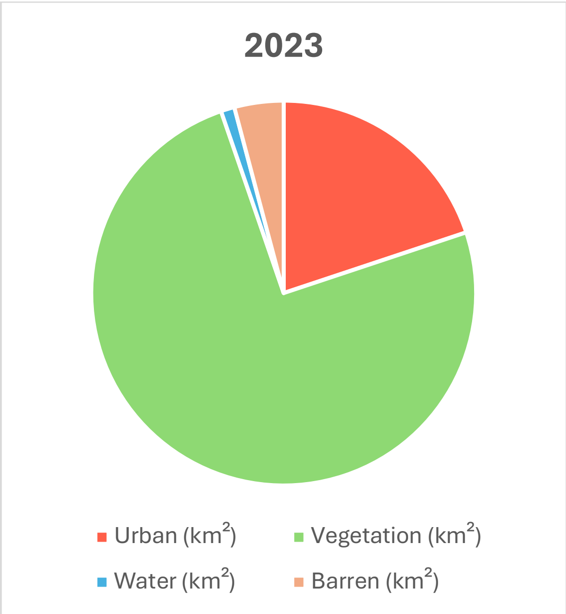


Figure 7 : Land Use Statistics for Pune for 2023

Year	Urban (km^2)	Vegetation (km^2)	Water (km^2)	Barren (km^2)
2015	208.41	1059.74	22.75	179.29
2020	231.47	1171.65	18.59	45.87
2023	291.9	1098.17	16.79	60.72

Table 3 : Change statistics for years 2015, 2020 and 2023

The LULC (Land use and land cover) maps of 2015, 2020 and 2023, the change map depicting the transformation of land-use patterns, and the change statistics will portray the ever-changing land cover of the city and its impact on vegetation and water bodies.

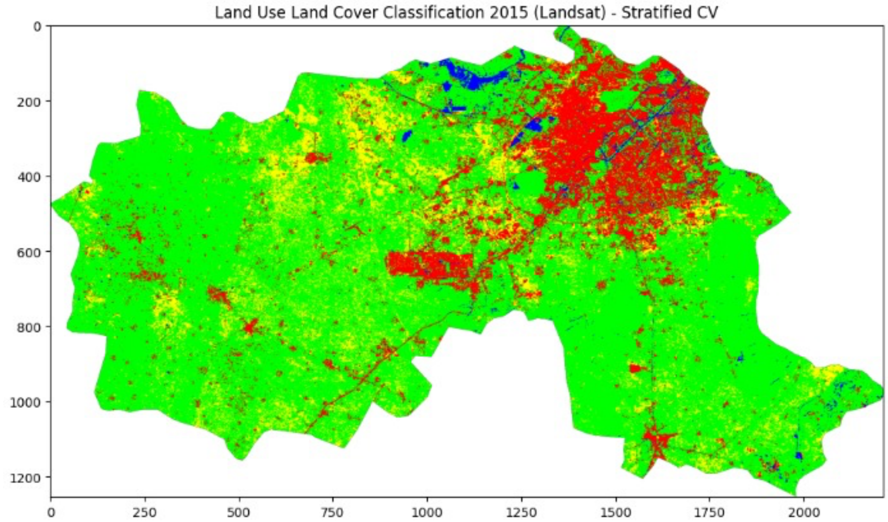


Figure 8 : Land Use Land Cover Classification 2015 (Landsat)

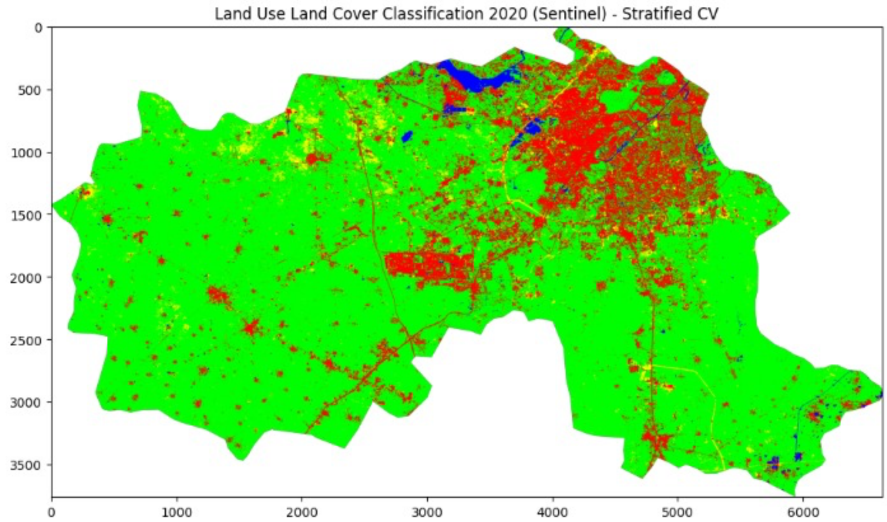


Figure 9 : Land Use Land Cover Classification 2020 (Sentinel-2)

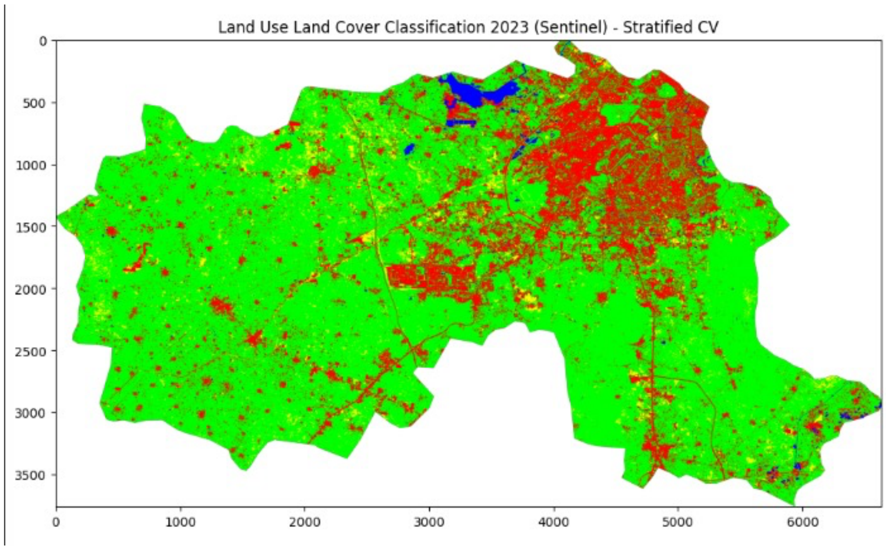


Figure 10 : Land Use Land Cover Classification 2023 (Sentinel-2)

The classification legend portrays the respective LULC class and their color codes. As reflected in the images, the red shaded area represents the urban area, Green represents the area under vegetation, blue areas denote water bodies, and yellow for barren land. The enormous expansion of the Built-up area from 2015 to 2023.

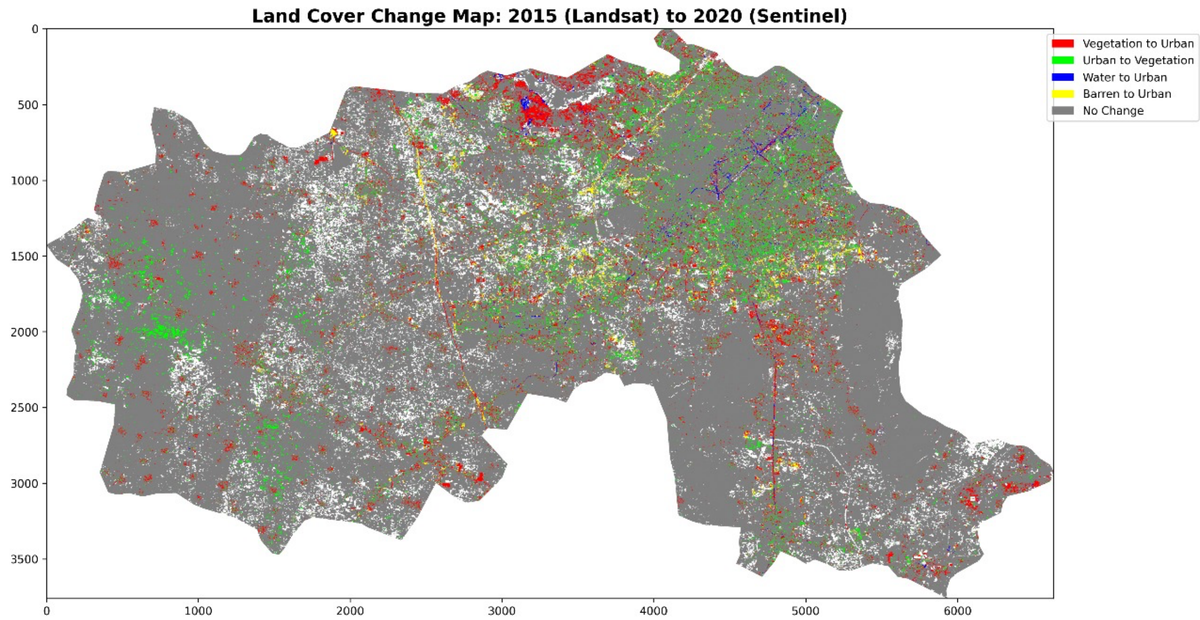


Figure 11 : Land Cover Change between 2015 to 2020

Period	Veg -> Urban	Water -> Urban	Barren ->Urban	Urban -> Veg	Urban -> Barren	Urban -> Water
2015–2020	67.0469	5.7224	15.8024	58.0734	5.1264	2.1428

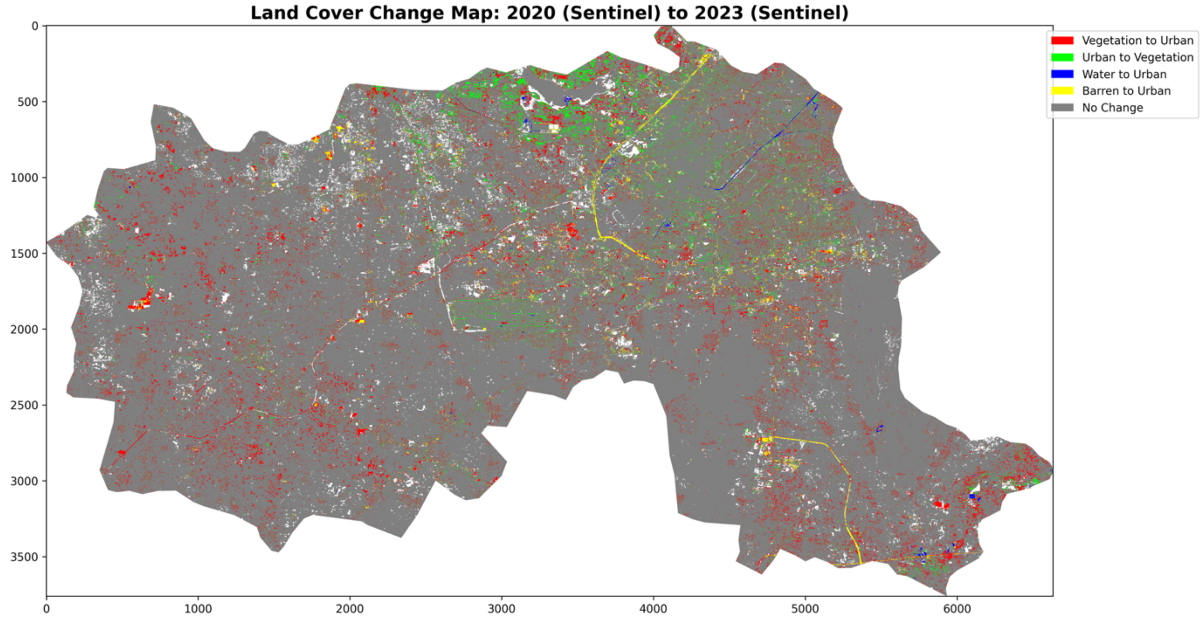


Figure 12 : Land Cover Change between 2020 to 2023

Period	Veg -> Urban	Water -> Urban	Barren ->Urban	Urban -> Veg	Urban -> Barren	Urban -> Water
2020–2023	86.8977	2.8339	12.2387	34.6181	4.3052	2.617

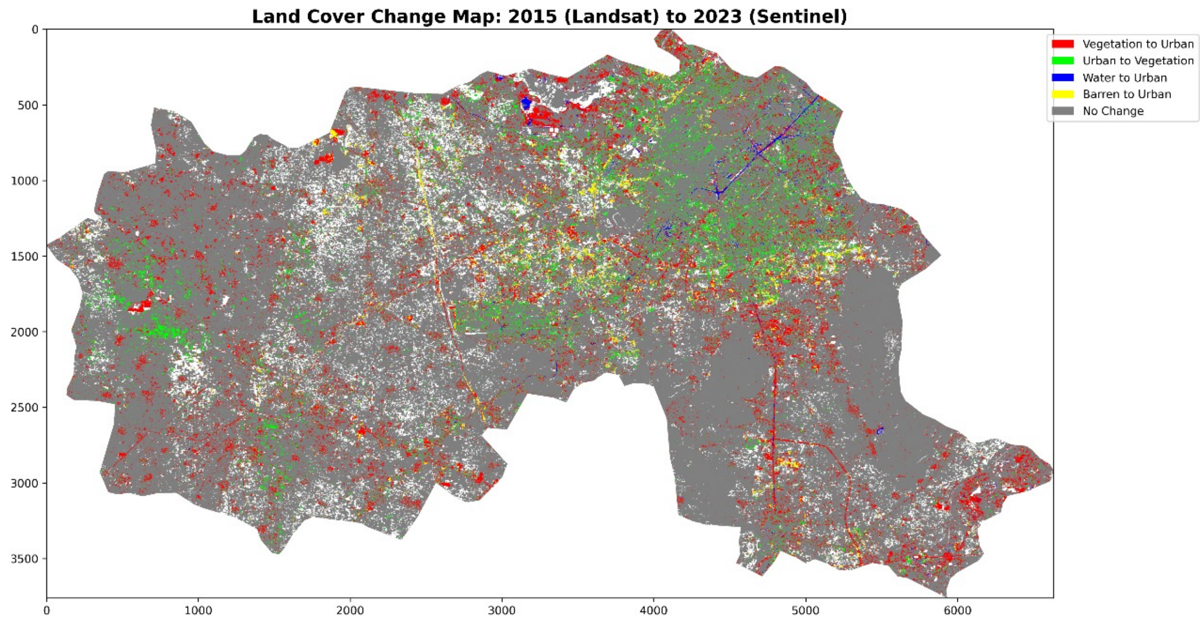


Figure 13 : Land Cover Change between 2015 to 2023

Period	Veg -> Urban	Water -> Urban	Barren ->Urban	Urban -> Veg	Urban -> Barren	Urban -> Water
2015–2023	115.1351	6.1849	22.6128	54.0515	4.3277	1.8962

We have detected changes and shown it on map. The map reveals scattered urbanization patterns with vegetation loss and gain, alongside some urban-to-vegetation conversion possibly indicating restoration efforts. While water-to-urban and barren-to-urban conversions appear less common, the predominance of gray areas suggests most land cover remained stable during this period, indicating that changes affect only a small percentage of the mapped region.

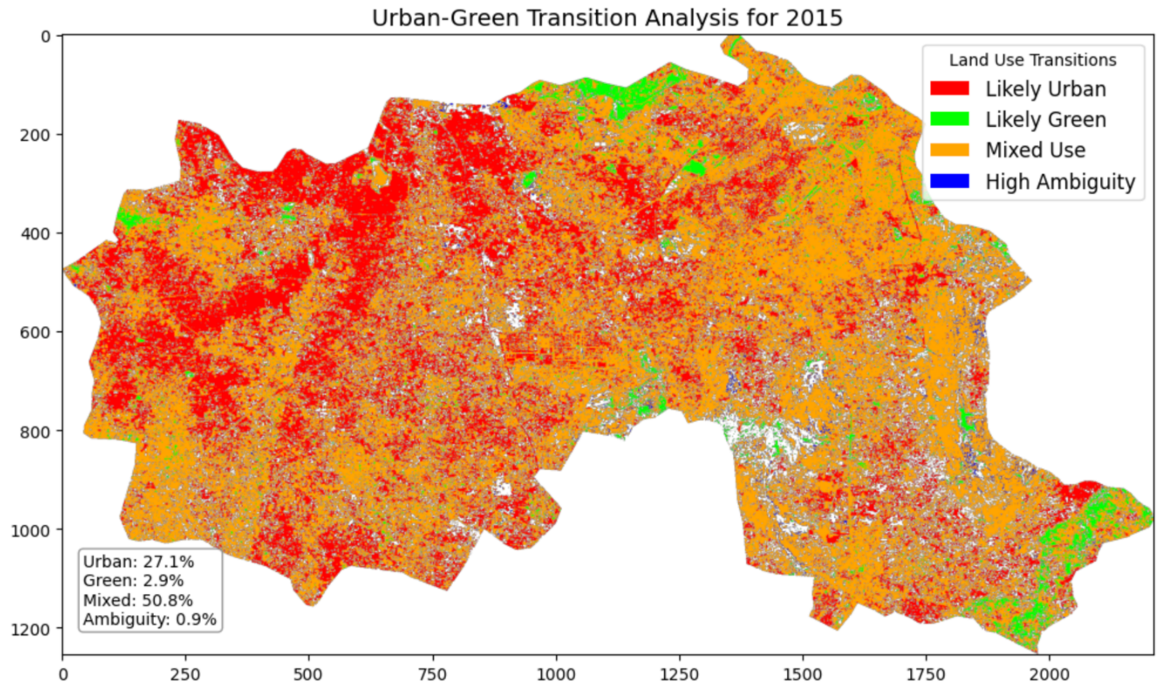


Figure 14 : Ambiguity Analysis using T-I-F of 2015

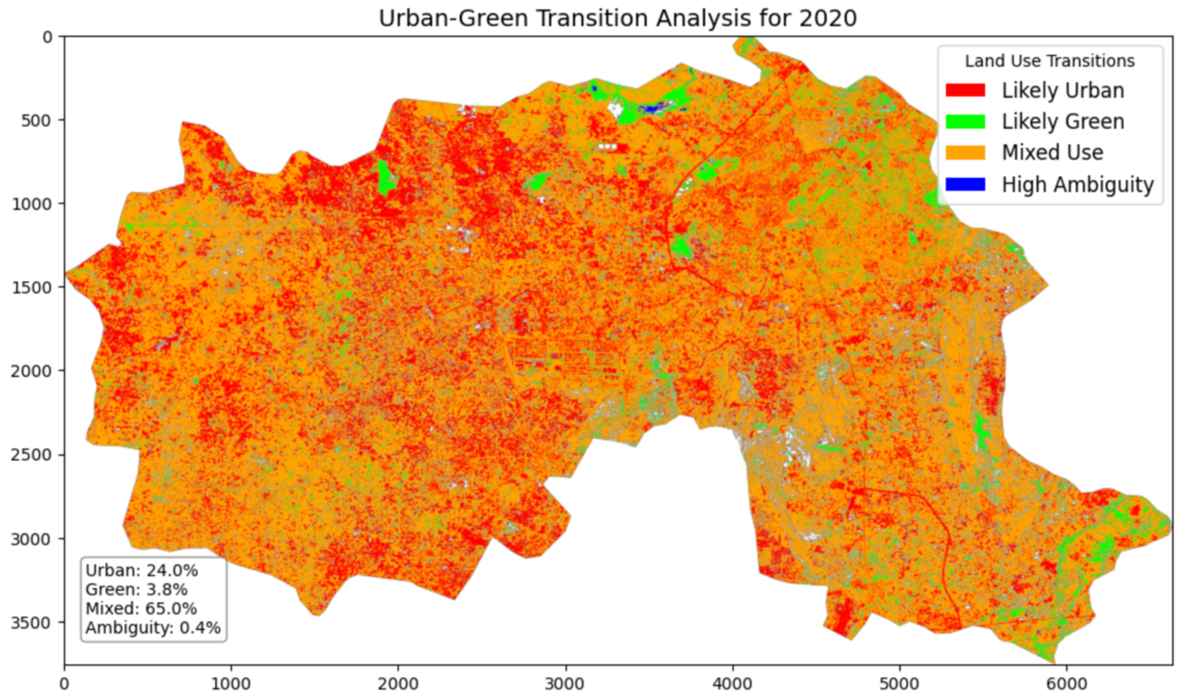


Figure 15 : Ambiguity Analysis using T-I-F of 2020

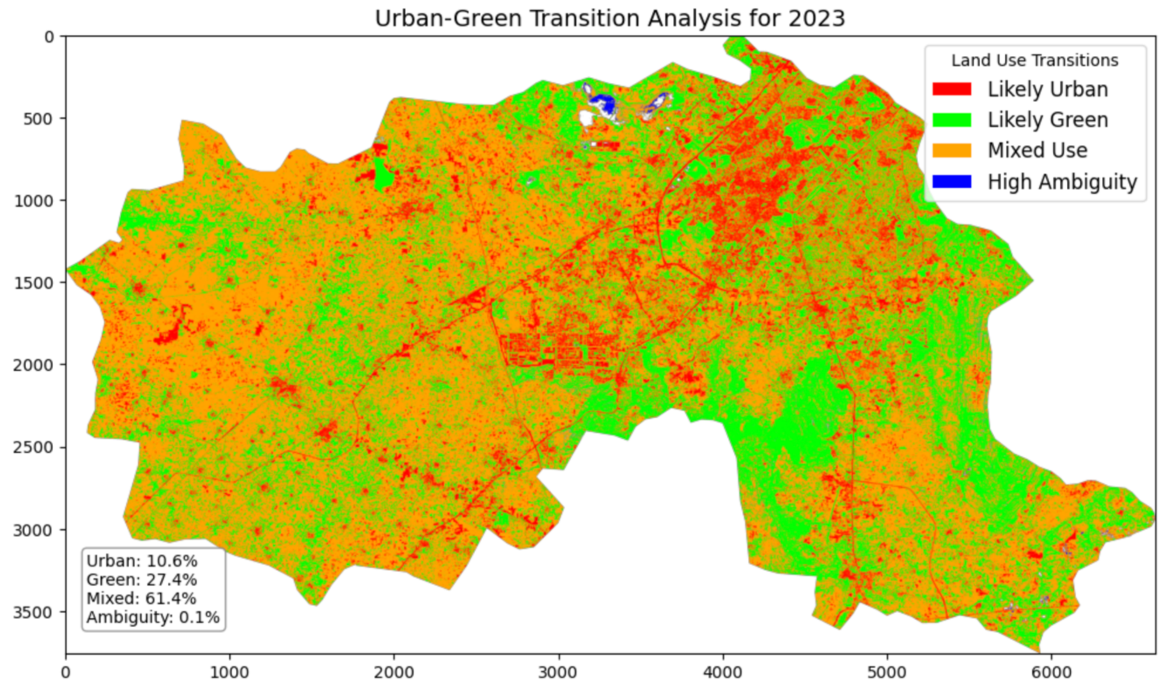


Figure 16 : Ambiguity Analysis using T-I-F of 2023

At last we performed ambiguity analysis to detect un-certainty in our work. T-I-F analysis reveals a significant shift in Gurgaon's urban-green dynamics. Urban likelihood (T) decreased from 0.674 (2015) to 0.469 (2023), while green space likelihood (F) increased from 0.540 to 0.599. Consistently high indeterminacy values (I > 0.81) indicate extensive transition zones throughout the study period. This suggests successful urban greening initiatives and increasingly complex peri-urban landscapes.

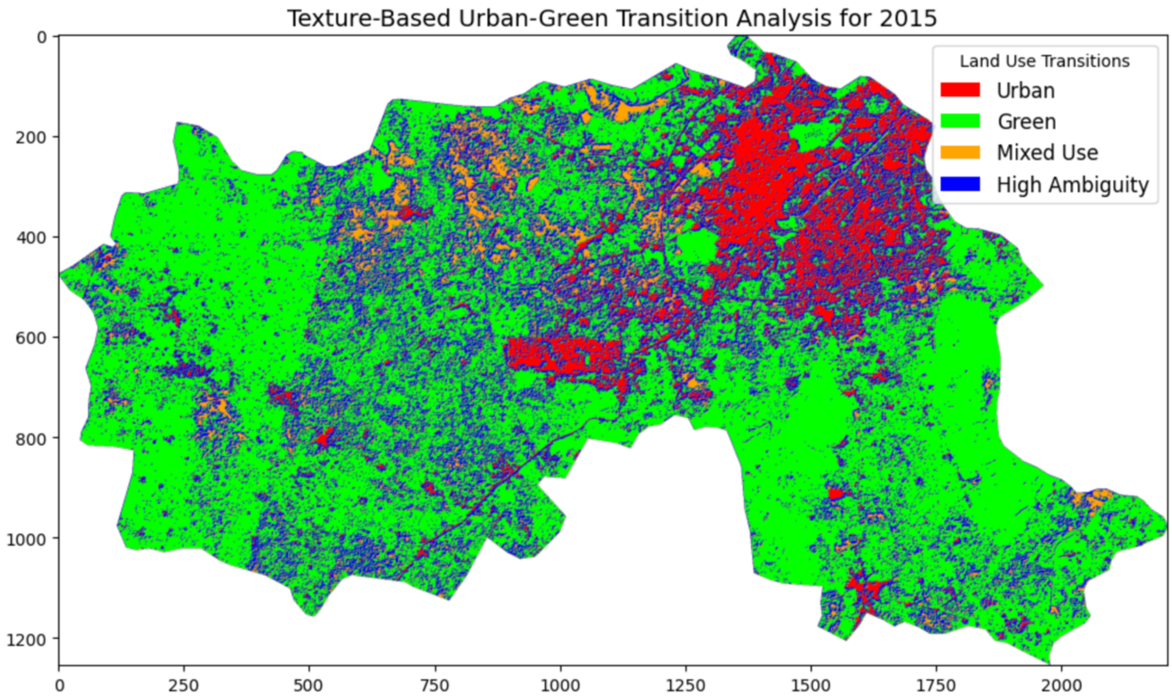


Figure 17 : Ambiguity Analysis using Texture based of 2015

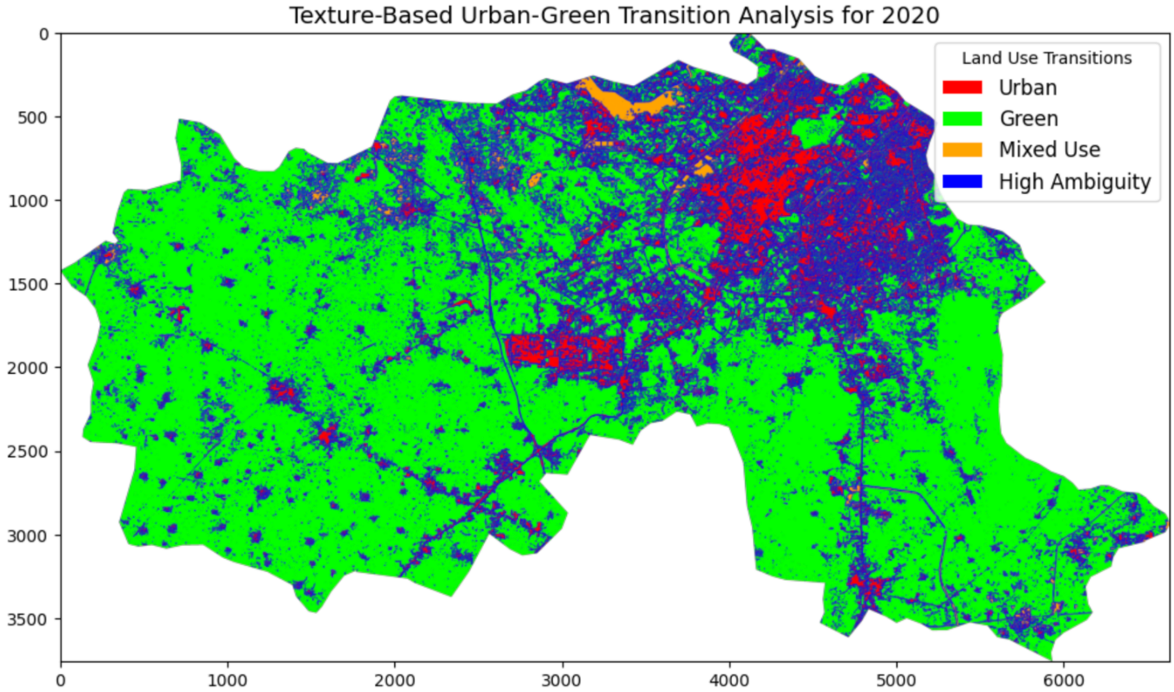


Figure 18 : Ambiguity Analysis Texture based of 2023

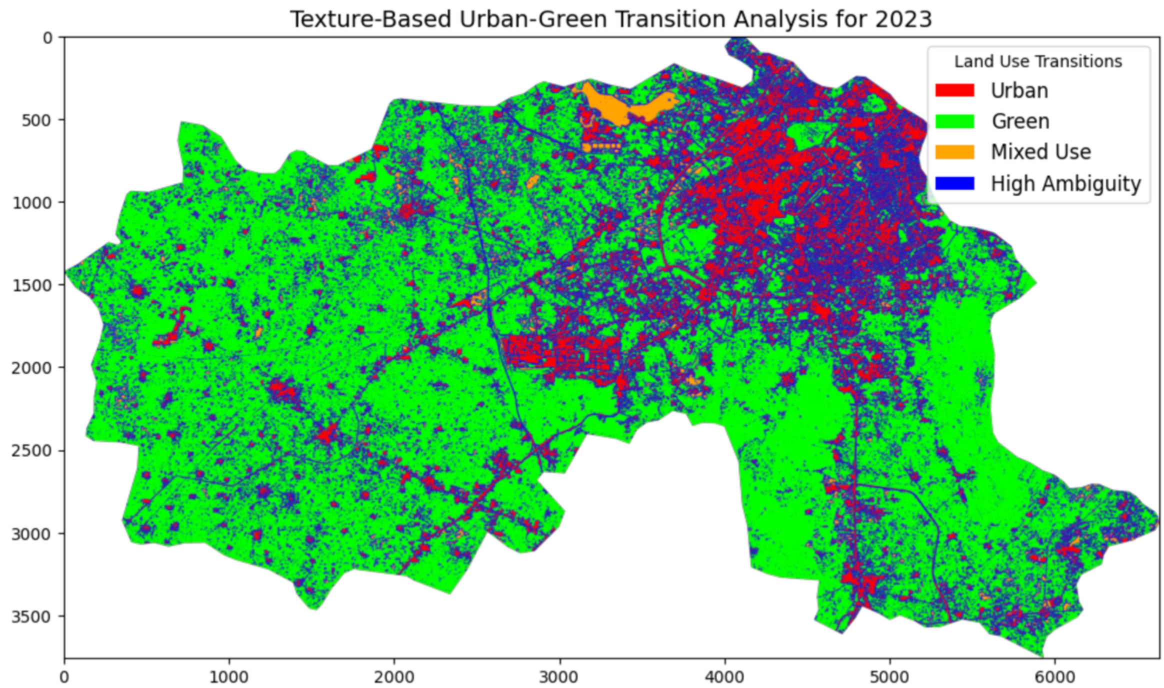


Figure 19 : Ambiguity Analysis Texture based of 2023

CONCLUSION

In Gurgaon over the eight-year period, with urban areas expanding by 40%, representing the highest rate of change among all land cover classes. This substantial urban growth has occurred primarily at the expense of barren land, which diminished by 66%, indicating a major shift in land use patterns across the region. The expansion follows the broader trend of rapid urbanization occurring in developing countries, particularly in satellite cities of major metropolitan areas.

Despite the intensive urbanization, vegetation showed remarkable resilience with a 3.6% net increase over the study period, though recent trends suggest some decline. This finding indicates that urban greening initiatives may have had some success in maintaining and even expanding green spaces within the developing urban fabric. The ambiguity analysis using Truth-Indeterminacy-Falsity (T-I-F) supports this observation, showing that urban likelihood (T) decreased from 0.674 in 2015 to 0.469 in 2023, while green space likelihood (F) increased from 0.540 to 0.599.

Water bodies faced considerable pressure throughout the study period, decreasing by 26% over eight years. This significant reduction raises concerns about water security and ecological health in the region, echoing similar findings in other rapidly urbanizing Indian cities like Pune, where water bodies shrank from 1.09% to 0.93% between 2001 and 2021.

The spatial analysis revealed scattered urbanization patterns with both vegetation loss and gain, alongside some urban-to-vegetation conversion that may indicate restoration efforts. The consistently high indeterminacy values ($I > 0.81$) throughout the study period suggest extensive transition zones and increasingly complex peri-urban landscapes. These transition zones represent critical areas where policy interventions for sustainable urban planning are most urgently needed.

The methodological approach combining Landsat 8 and Sentinel-2 imagery with machine learning classification proved highly effective, achieving 97% training accuracy, 94% overall accuracy, and a Cohen's Kappa coefficient of 87%. This robust analytical framework provides a reliable foundation for monitoring urban change and supporting evidence-based urban planning decisions.

In conclusion, Gurgaon's rapid urbanization between 2015 and 2023 has significantly transformed the landscape, with complex patterns of urban expansion, vegetation resilience, and water body reduction. The findings highlight the need for integrated urban planning approaches that balance development needs with environmental conservation, particularly in managing the critical urban-green interfaces identified through the ambiguity analysis. This study demonstrates the value of remote sensing technologies in monitoring urban development and provides essential information for sustainable planning in rapidly developing cities like Gurgaon.

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