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Monitoring of Dynamic Changes in Land Use and Land Cover in Faridabad District Using Multi-Temporal Satellite Data and Geospatial Techniques

Vachaspati Pandey[1]* and Manthena Prashanth[2]

[1]*Discipline of Geology, School of Sciences, IGNOU, New Delhi 110068, India*
[2]*Department of Applied Geology, Central University of Karnataka, Kalaburagi 585367, Karnataka, India*

Abstract

Land use and land cover (LULC) change can be effectively analyzed using digital change-detection techniques applied to multi-temporal satellite imagery. This study examines spatio-temporal LULC changes in Faridabad District, India from 2001 to 2022 by leveraging multi-temporal Landsat satellite data and geospatial techniques. A supervised classification approach was employed to classify the landscape into six LULC categories for each time point, followed by the creation of change matrices to quantify transitions. The results indicate rapid urban expansion alongside significant losses in agricultural land, vegetation, and water bodies. Landsat-5 TM, Landsat-7 ETM+, and Landsat-8 OLI data were utilized to map these changes. Notably, built-up area increased dramatically over the study period while agricultural areas and other vegetated or fallow lands declined. This study demonstrates the utility of long-term satellite data for monitoring dynamic LULC changes and provides insights into the patterns of urbanization and land transformation in the region.

Keywords: land use; land cover; change detection; spatio-temporal; supervised classification; remote sensing

Introduction

Land use and land cover (LULC) changes are an important indicator of the state of Earth's resources and can be efficiently monitored with remote sensing (RS) data. Satellite-based observations regularly provide large volumes of data over extensive areas at a relatively low cost compared to field surveys. These technologies are essential for examining the effects of climate change because land use strongly impacts both the carbon cycle and surface energy balance. Advances in satellite sensors and imaging techniques have made LULC studies more accurate and useful for planners and decision-makers. The overarching goal is to precisely monitor and quantify changes in natural and anthropogenic land use over time, which is crucial for environmental management and for modeling the Earth system.

Land use patterns are continually shaped by human interventions (e.g. population growth, agriculture, urbanization) as well as natural processes. Consequently, accurate and up-to-date information on LULC changes is critical for effective planning and decision-making. Understanding where and how LULC is changing helps reveal the interactions between human activities and natural systems, enabling more informed resource management decisions.

Geospatial techniques using multi-temporal remote sensing data have been widely applied to monitor LULC changes at local and global scales. Medium-resolution satellite imagery such as the Landsat series is among the most popular data sources for tracking and mapping land-cover changes. Numerous studies have successfully used Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), and Enhanced Thematic Mapper Plus (ETM+) data to monitor LULC dynamics, especially in areas experiencing significant human activity. For example, Zaki et al. (2011) utilized Landsat TM imagery to detect land-cover changes in newly urbanized zones of northeast Cairo, Egypt. Multi-sensor data from other satellites have likewise proven effective for monitoring LULC change. In general, multi-temporal remotely sensed data with high revisit frequency and suitable spectral/spatial resolution provide a crucial basis for change-detection analyses [1]. The typical change-detection workflow includes identifying the location and type of changes, quantifying the extent of changes, and assessing the accuracy of the change-detection results.

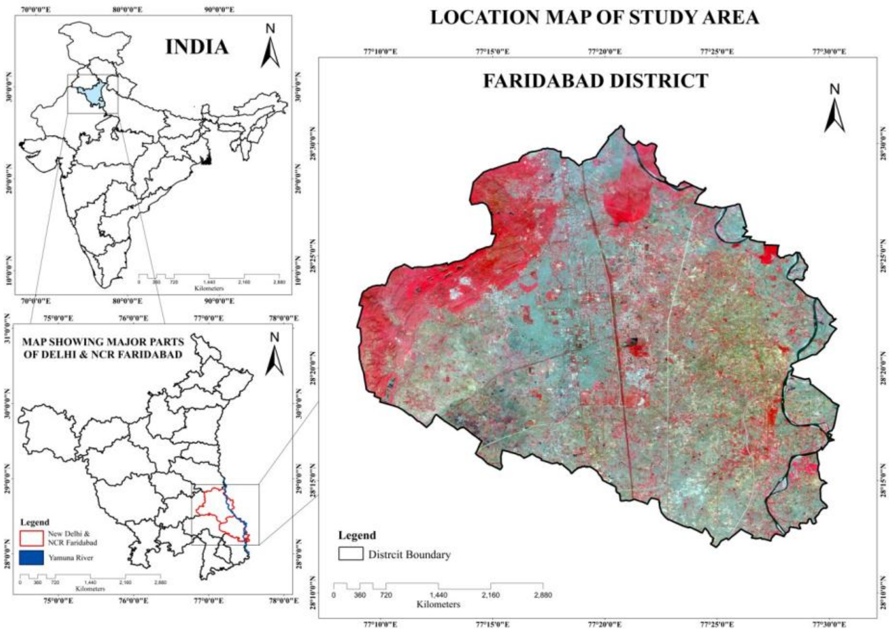
Proper urban planning requires integrating appropriate spatial data, as urban expansion and LULC changes will continue to occur over time and space [2]. It is difficult to analyze urbanization impacts without geospatial information. Many researchers have attempted large-scale urban growth studies; however, the lack of site-specific data often limits detailed analysis of peri-urban areas in developing countries [3].

Recent advancements in geospatial technology enable quantitative analysis of urban expansion patterns. Satellite data can be used to monitor landscape changes in a short time and at an affordable cost [4]. High-resolution imagery and advanced image-processing models allow frequent updates of land use patterns on the ground [5]. These techniques significantly improve the classification of LULC and the detection of urban growth.

Several studies have explored urban growth and LULC changes in rapidly urbanizing Indian cities using geospatial techniques. Bhatta (2010) analyzed urban sprawl in Kolkata using a cellular automata model to project expansion trends up to 2040. Ramachandra et al. [6] employed geoinformatics and spatial metrics to study the urban structure and spatiotemporal expansion of Kolkata. Mondal et al. (2016) integrated cellular automata and Markov chain models to simulate urban development in the Kolkata agglomeration. These studies underscore the capability of remote sensing and GIS methods to capture urbanization dynamics over time. In light of these advances, the present study applies a similar multi-temporal geospatial approach to assess LULC changes in Faridabad District.

Study Area

The study area is Faridabad District, located in the Aravalli hill region of Haryana state, India, and part of the National Capital Region (NCR). It lies between longitudes 77°04′39″E and 77°32′50″E, and latitudes 27°51′15″N and 28°30′52″N. The district covers an area of approximately 742.90 km². Faridabad is bordered by the National Capital Territory of Delhi to the north, Gurugram District (Haryana) to the west, Gautam Budh Nagar District (Uttar Pradesh) to the east, and Mathura District (Uttar Pradesh) to the south. A major highway (Sher Shah Suri Marg, part of National Highway 2) passes through the center of the district from north to south. **Figure 1** shows a location map of the study area. *(Note: The study area boundary shapefile was obtained from Survey of India.)*



**Note: - The Sources of study area shp (shapefile) used in this study from: SOI (Survey of India)*

Figure. 1: Location Map of the Study area

Data Used and Methodology

In this research, multi-temporal Landsat satellite imagery was used to analyze LULC changes. Five cloud-free Landsat scenes (Table 1) from the Landsat-7 ETM+, Landsat-5 TM, and Landsat-8 OLI/TIRS sensors, covering the years 2001, 2003, 2011, 2016, and 2022, were obtained from the USGS archives. The imagery was processed using ERDAS Imagine 14.0, ArcGIS Pro, and ArcGIS 10.4.1 software. After data acquisition, the individual spectral bands for each date were layer-stacked to form composite images. Adjacent scene composites were mosaicked to cover the entire district, then the mosaics were radiometrically corrected and reprojected to the UTM coordinate system (WGS 84 datum). Each image mosaic was finally subset to the Faridabad district boundary for analysis.

Table 1. Landsat datasets used for LULC mapping in Faridabad District.

S.No.	Satellite	Date of Acquisition	Path/Row	Resolution (m)
1	Landsat-7	02/04/2001	142/42 & 142/43	30

S.No.	Satellite	Date of Acquisition	Path/Row	Resolution (m)
	ETM+			
2	Landsat-7 ETM+	06/04/2003	142/42 & 142/43	30
3	Landsat-5 TM	06/04/2011	142/42 & 142/43	30
4	Landsat-8 OLI/TIRS	21/05/2016	142/42 & 142/43	30
5	Landsat-8 OLI/TIRS	30/04/2022	142/42 & 142/43	30

Land use/land cover maps were generated through supervised classification of the Landsat images. Six LULC classes were defined for the study area: **Water Bodies**, **Agricultural Land**, **Mixed Forest Land**, **Built-up Area**, **Barren Land**, and **Fallow Land/Sandy Area**. Initial pixel-based classification results often exhibited spectral confusion among certain classes due to similar reflectance characteristics. For example, fallow agricultural fields, open scrub forests, settlements, and barren lands were sometimes misclassified as each other or as other land types. To improve classification accuracy, a post-classification sorting process was employed. Misclassified regions were corrected by digitizing polygons for the appropriate classes and updating the classified maps accordingly.

Land-cover change detection was carried out by comparing the classified LULC maps from different years. Two approaches were used to identify changes: (1) overlaying the vectorized LULC maps from successive years to visually highlight areas of change, and (2) computing a multi-date change detection matrix. The classified maps from 2001, 2003, 2011, 2016, and 2022 served as inputs for change analysis. Using the Change Detection Matrix tool in ERDAS Imagine 10.4, transitions between the six classes were quantified for each time interval. Additionally, a mid-decade change analysis (e.g. 2011–2016) was performed to capture intermediate dynamics. A class-wise change matrix (gain/loss) was compiled in a spreadsheet to calculate the area gained or lost by each category over each period.

Accuracy assessment of the classified maps was performed to validate the results. The classified LULC maps were compared with reference data—including high-resolution Google Earth imagery, existing land-use maps, and field observations—to evaluate classification accuracy. An error confusion matrix was generated for each map, and standard accuracy metrics were derived. The overall classification accuracy of the maps was calculated as the number of correctly classified pixels divided by the total number of reference pixels, expressed as a percentage. User's accuracy and producer's accuracy were computed for each LULC class: user's accuracy represents the proportion of a class's mapped pixels that are correctly classified, while producer's accuracy represents the proportion of reference pixels of a given class that are correctly mapped. The Kappa coefficient (κ) was also calculated to measure the agreement of the classification with the reference data beyond random chance [7].

Results and Discussion

For the 2022 LULC classification, the overall mapping accuracy achieved was **93.22%**, with a Kappa coefficient of approximately **91%** (Table 4). The user's and producer's accuracies for most classes were above 90%, except for the Barren Land category which had a producer's accuracy of about 65% (Table 4). This indicates a high reliability of the classified maps, providing confidence in the change-detection analysis that follows.

LULC maps were generated for five points in time [8], and the area under each land-use category for these years is given in Table 2. The study area was classified into six major LULC classes as noted above. Over the two-decade study period, each class experienced changes in extent, with both increases and decreases observed at different times (Table 3). Figure 2 illustrates the spatial distribution of LULC in Faridabad District for the selected years.

Urban or built-up areas expanded markedly over time at the expense of agricultural land. Built-up area increased from about 18.14% of the district in 2001 to 28.03% in 2022 (Table 2). This growth of settlements and infrastructure was most pronounced around Faridabad city and along major transportation corridors, reflecting the pressures of urbanization. Correspondingly, agricultural land cover declined substantially, dropping from 51.60% in 2001 to 39.06% by 2022 (Table 2). Much of this formerly cultivated land has been converted to urban uses. The largest losses of agricultural area occurred in the early 2000s and early 2010s (a reduction of approximately 3.95 percentage points by 2003, and a further 4.34 points by 2011; Table 3), although the rate of loss slowed slightly after 2011.

Water bodies in the district (including rivers, lakes, and ponds) showed a slight overall decline. They constituted 1.38% of the area in 2001 and 1.40% in 2022, but fluctuated marginally in between (Table 2). These small changes in water coverage may be related to the operation of canal networks for irrigation and seasonal variability in rainfall. Fallow land and sandy areas have decreased more noticeably. Fallow/sandy areas covered about 3.09% of Faridabad in

2001, but only 0.49% in 2022 (Table 2). An initial slight increase in fallow land was observed up to 2011 (rising to ~3.30%), likely as some agricultural fields lay uncultivated or became sand-dominated. However, by 2016 and 2022 many of these sandy or barren patches were converted to other uses, leading to a net decline in fallow land (Table 3). Overall, the sandy riverbank regions (sand bars along the Yamuna River) have not changed significantly in extent over the study period.

Areas classified as mixed forest (largely the wooded portions of the Aravalli hills and plantations) have increased slightly over time. Forest cover expanded from about 11.40% in 2001 to 15.32% in 2022 (Table 2). This positive change could be due to afforestation efforts or natural regrowth in some hilly areas of the district. Barren land (rocky or uncultivated open land) remained relatively stable in terms of overall area. It constituted 14.39% in 2001 and 15.69% in 2022 (Table 2), with a minor dip in the mid-2000s followed by a slight increase by 2016. Some barren lands may have been converted to built-up use, while elsewhere new barren areas emerged where agriculture or fallow land was abandoned. In general, aside from the major urban growth and associated agricultural decline, changes in forest, barren, and water categories were less pronounced.

Table 2. Area distribution (%) of land use/land cover classes in Faridabad District (2001–2022).

LULC Class	**2001**	**2003**	**2011**	**2016**	**2022**
Water Bodies	1.38	1.44	1.24	1.43	1.40
Agricultural Land	51.60	47.65	43.31	40.48	39.06
Mixed Forest Land	11.40	13.33	15.14	15.30	15.32
Built-up Area	18.14	21.03	23.52	26.53	28.03
Barren Land	14.39	13.45	13.49	15.71	15.69
Fallow Land/Sandy Area	3.09	3.11	3.30	0.55	0.49
Total	**100**	**100**	**100**	**100**	**100**

Table 3. Percentage change in area of each LULC class during different periods.

LULC Class	2001–2003	2003–2011	2011–2022
Water Bodies	-0.06	0.20	-0.16
Agricultural Land	3.95	4.34	4.25
Mixed Forest Land	-1.93	-1.81	-0.18
Built-up Area	-2.89	-2.49	-4.51
Barren Land	0.94	-0.04	-2.20
Fallow Land/Sandy Area	-0.02	-0.19	2.81

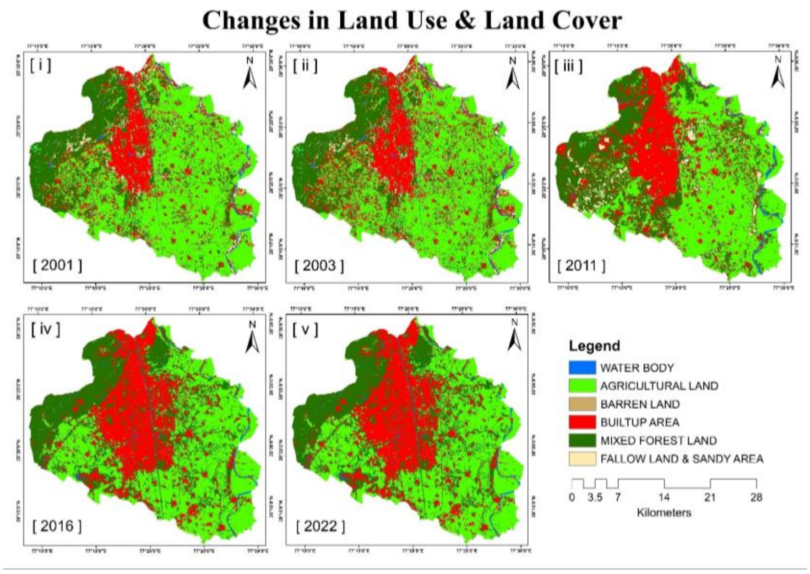


Figure 2. Land use/land cover maps of Faridabad District for the years (i) 2001, (ii) 2003, (iii) 2011, (iv) 2016, and (v) 2022.

Table 4. Accuracy assessment of the LULC classification.

Class	**User's Accuracy (%)**	**Producer's Accuracy (%)**
Water Bodies	93.75	100.00
Built-up Area	95.24	96.15
Barren Land	100.00	65.00
Fallow Land/Sandy Area	83.87	92.86
Mixed Forest Land	89.74	92.11
Agricultural Land	94.44	94.44
Overall Accuracy	**93.22**	—
Kappa Coefficient	**91.14**	—

Conclusion

This research demonstrated the effectiveness of multi-temporal remote sensing data and geospatial techniques for mapping and detecting LULC changes in Faridabad District. The use of multi-temporal Landsat imagery provided a precise and affordable means of monitoring land use changes over the 2001–2022 period. The findings clearly show distinct patterns and trends of land transformation in the area, underscoring the importance of long-term satellite data for environmental monitoring.

By analyzing and classifying the satellite data into six LULC classes and performing post-classification change detection, we identified changes across all classes. The change-detection approach (based on comparing classified maps) proved to be effective, capturing subtle land transformations better than independent classification of each date would. Urban sprawl was the most dominant change observed, far exceeding changes in any other category. According to the study, rapid urban expansion has resulted in a notable decline in agricultural and fallow lands as well as overall green cover in the district.

Several factors are responsible for the rapid growth of urban areas in Faridabad. Population growth, rural-to-urban migration, and broader economic development in and around Faridabad city have together fuelled the conversion of rural and natural lands into urban uses. The combined findings of this study provide policymakers and planners with scientific evidence of how land use has changed, helping them to identify potential issues (such as loss of cultivable land or wetlands) and opportunities for sustainable land management in the region.

Future studies could build on this work by utilizing higher-resolution or more frequently acquired satellite images to achieve even higher accuracy in change detection. Extending the analysis to include additional time steps or integrating predictive modelling (e.g. cellular automata or machine learning approaches) would further aid in understanding and managing the trajectory of land use change in Faridabad and similar fast-growing areas.

Conflicts of Interest: The authors declare no conflict of interest.

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