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QUANTIFY CHANGES IN AGRICULTURE LAND USING SUPERVIESD CLASSIFICATION METHOD FOR REWARI DISTRICT, HARYANA

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Abstract: Land is a paramount natural resource. The city's population increases, accompanied by changes in geographic dimensions. Nevertheless, it is impossible to impede the natural process of land transformation. This study examines the evolution of highways. A change detection model was executed in ERDAS. Envision assessing land usage and land cover, particularly agricultural land, from 2006 to 2021. Five forms of land use were identified, with built-up agricultural land as the most prevalent type. A notable transformation has been recorded during 16 years (2006-2021) in Deodhai hamlet, situated 10 km from Rewari, Haryana, enabled by ERDAS, subsequent to the completion of the NH-48 highway. In 2006, 61.78% of the land was allocated for agricultural use, declining to 48.67% by 2021. The principal reason driving this alteration in land use is road construction.

Keywords Agriculture Land**,** ERDAS, Google Earth Pro, QGIS land use land cover (LULC), NH-48

1. Introduction. The fundamental goal of roads is to facilitate the development of a city or region while also promoting growth in the production and service sectors. Road infrastructure attracts greater development. The recent construction of highways facilitates the advancement of the states. The development of a city or region, along with the expansion of its production and service sectors, is predominantly facilitated by road infrastructure. The correlation between road infrastructure development and alterations in land use surrounding it warrants thorough investigation. The construction of highways facilitates the advancement of states towards growth. Constructing roads is an endeavor that pertains to advancing the nation's development [1-5].

The development of roadways facilitates urban expansion. Facilitating relocation enables timely and efficient delivery of goods to individuals.

2.Literature Review:

Numerous researchers worked on land use cover classification for the quantification of various land use classes.

2.1 Data Sources for LULC

Remote sensing data for LULC classification can be obtained from diverse platforms, including satellites, airborne sensors, and UAVs (Wulder et al., 2008). By use of High-resolution sensors, such as SPOT, IKONOS, and QuickBird detailed mapping can be done (Lu & Weng, 2007).

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Sentinel-2 and WorldView series satellites have offered improved spatial and spectral resolution (Drusch et al., 2012). Synthetic Aperture Radar (SAR) systems, have further expanded possibility of LULC analysis by penetrating cloud cover and providing information (Lee & Pottier, 2009).

2.2 Classification Techniques for Landuse and Landcover analysis

1. Pixel-Based Methods(DN value based) : Pixel-based classification methods, supervised and unsupervised approaches, are widely used for LULC mapping. (Lillesand et al., 2015). However, its less realible when there are wide range of classes and distributed DN values (Foody, 2002).
2. Object-Based Image Analysis (OBIA): it is an alternative of pixel-based methods, leveraging both spectral and spatial information. By segmenting imagery into meaningful objects, OBIA reduces the "salt-and-pepper" effect common in pixel-based classifications (Blaschke, 2010).
3. Machine Learning Approaches: Several Machine learning classifiers, such as decision trees, random forests (RF), support vector machines (SVM), and artificial neural networks (ANNs), have become increasingly dominant. (Pal, 2005). RF is used for discrete data, SVMs, on the other hand, excel in small sample sizes and non-linear separability (Mountrakis et al., 2011).
4. Deep Learning Techniques. CNNs extract hierarchical features directly from imagery, outperforming traditional approaches in complex environments (Zhu et al., 2017). Applications of deep learning have been demonstrated in urban growth modeling, forest cover monitoring, and agricultural land classification (Ma et al., 2019). Despite their success, deep learning methods require substantial computational resources and large labeled datasets, which can limit their applicability in some contexts.

2.3 Applications of LULC Classification

LULC classification has broad applications across environmental and socio-economic domains:
- Urban Planning: Mapping urban expansion supports sustainable city planning (Herold et al., 2003).
- Agriculture: Remote sensing aids in crop monitoring, yield prediction, and land suitability assessments (Thenkabail et al., 2009).
- Forestry: LULC classification contributes to deforestation monitoring, forest fire mapping, forest biomass estimation, and biodiversity assessments (Hansen et al., 2013).
- Hydrology: RS-based LULC data are integral to hydrological modeling, particularly for runoff prediction and watershed management and flood management (Niehoff et al., 2002).
- Climate Change Studies: LULC changes influence carbon cycles and climate models, making accurate classification essential for global environmental monitoring (Foley et al., 2005).

2.4 Challenges and Limitations

Despite advances, several challenges persist in LULC classification:
1. Mixed Pixels: In medium-resolution imagery, mixed pixels reduce classification accuracy, especially in heterogeneous landscapes (Fisher, 1997).
2. Spectral Confusion: Different land cover types often exhibit similar spectral signatures, leading to misclassification (Foody, 2002).

3. Data Integration: Combining optical, radar, and LiDAR data poses technical and methodological challenges (Li et al., 2013).
4. Computational Demand: Advanced techniques, particularly deep learning, require high computational resources (Zhu et al., 2017).
5. Ground Truth Data: The availability and quality of reference data remain a critical factor in achieving reliable classifications (Congalton & Green, 2008).

Comparative Overview of Classification Methods

See table below.

Method	Advantages	Limitations	Applications
Pixel-Based (MLC, k-means)	Simple, widely used, computationally light	Low accuracy in heterogeneous areas	Early LULC studies, baseline maps
OBIA	Incorporates spatial context, reduces noise	Sensitive to segmentation parameters	Urban mapping, detailed landscapes
Machine Learning (RF, SVM)	High accuracy, handles complex data	Requires parameter tuning, training data	Agriculture, forestry, biodiversity
Deep Learning (CNNs)	Superior accuracy, hierarchical features	Data- and resource-intensive	Urban growth, climate monitoring

Remote sensing has transformed LULC classification, evolving from pixel-based methods to advanced machine learning and deep learning approaches. While traditional methods remain useful for baseline studies, modern techniques offer greater accuracy and robustness, particularly when combined with multi-source data. Challenges such as mixed pixels, data integration, and computational demand persist, but innovations in data fusion and cloud computing continue to address these barriers. Future research will likely focus on harmonizing multiple data types, enhancing transferability across regions, and leveraging AI-driven methods to provide near real-time LULC monitoring.

In this paper Supervised classifiaction using GIS method is used, where sample datset is provided for each class based on theses sample dataset classification is done.the work is done to quantify role of develoment of infrastructure on land Basically agriculture and barren land.

3. Study Area : The stretch used in the search lies between Deodhai village to Harchandpur village (NH-48) and is located 10 km away from Rewari City in the southern part Haryana, India . It is located at an area extending from 28° 07'31.06" N to 28° 04' 53.84" N latitude and from 76° 38'10.56 " E to 76° 34' 21.06" E Longitude.

4.Methodology:

We employed Google Earth Pro to evaluate and identify land use and land cover from aerial imagery of the region. The imaging data spans a period of 16 years, from 2006 to 2021. This study employed Google Earth Pro, QGIS, and ERDAS Imagine 2014 software. After the supervised classification of images using ERDAS Imagine 2014 for the years 2006, 2014, and

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2021, we saw substantial changes in arable land, desolate areas, developed regions, and aquatic environments.

Table 1: Software Used

Software	Function
Google Earth Pro	Data Capture , data visualization, data Creation, Real – time streaming
Q GIS	Displays multiple layers , geo references
ERDAS Imagine 2014	Simplifies image classification (supervised & Unsupervised classification), image interpretation.

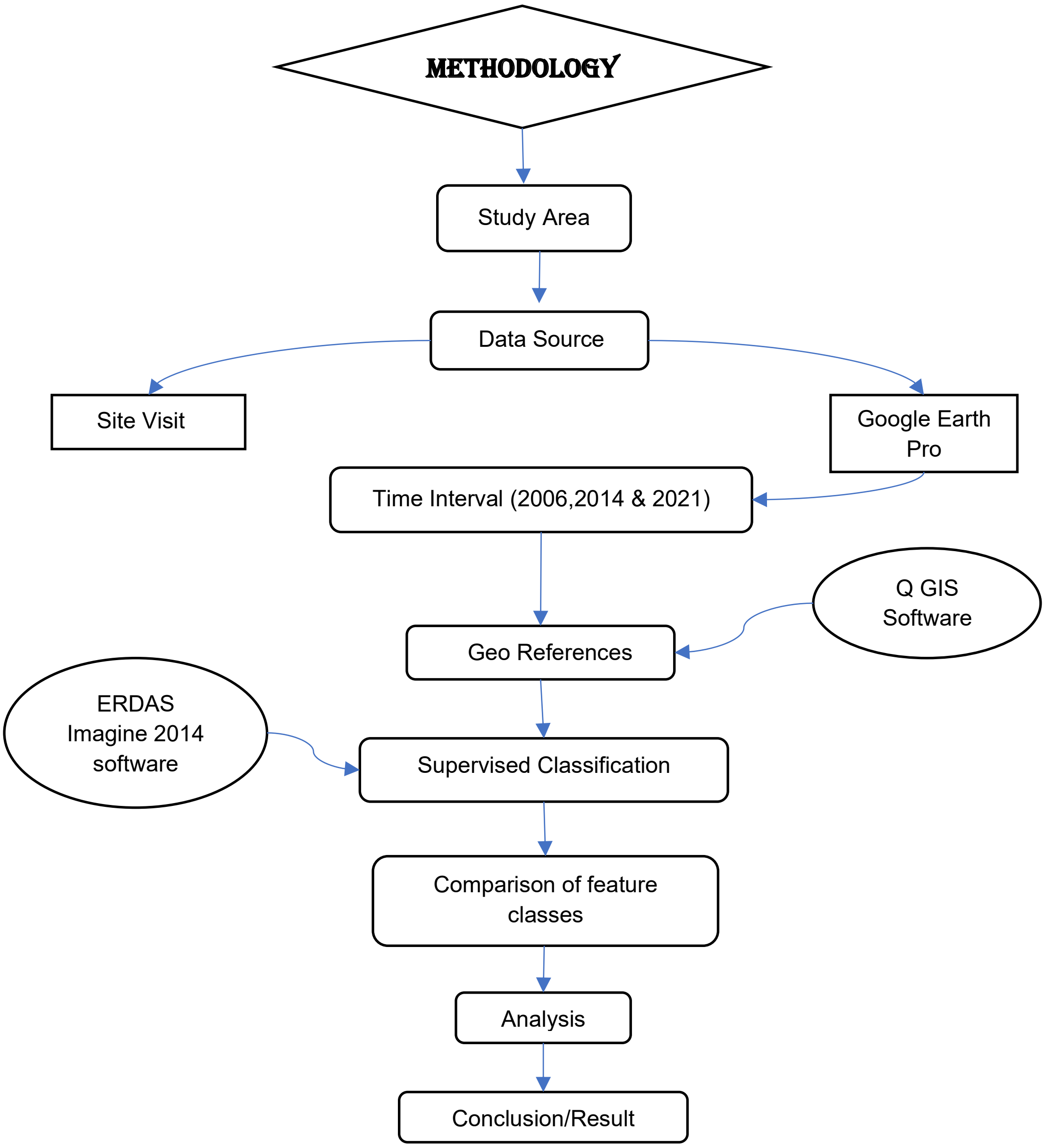

Fig 1 Methodology Flow Chart

5. Data Analysis:

The main data used in this study is an aerial image of a road development area .These images are obtained based on a database from Google Earth pro The road section that are analyzed in this study is from Deodhai village to the Harchandpur village expressway the length of road stretch of site is 7.87km with six-lane two-way divided expressway.

5.1 Location of study area

The pictures of the Rewari district NH-48 which was taken by the google earth pro follows as:

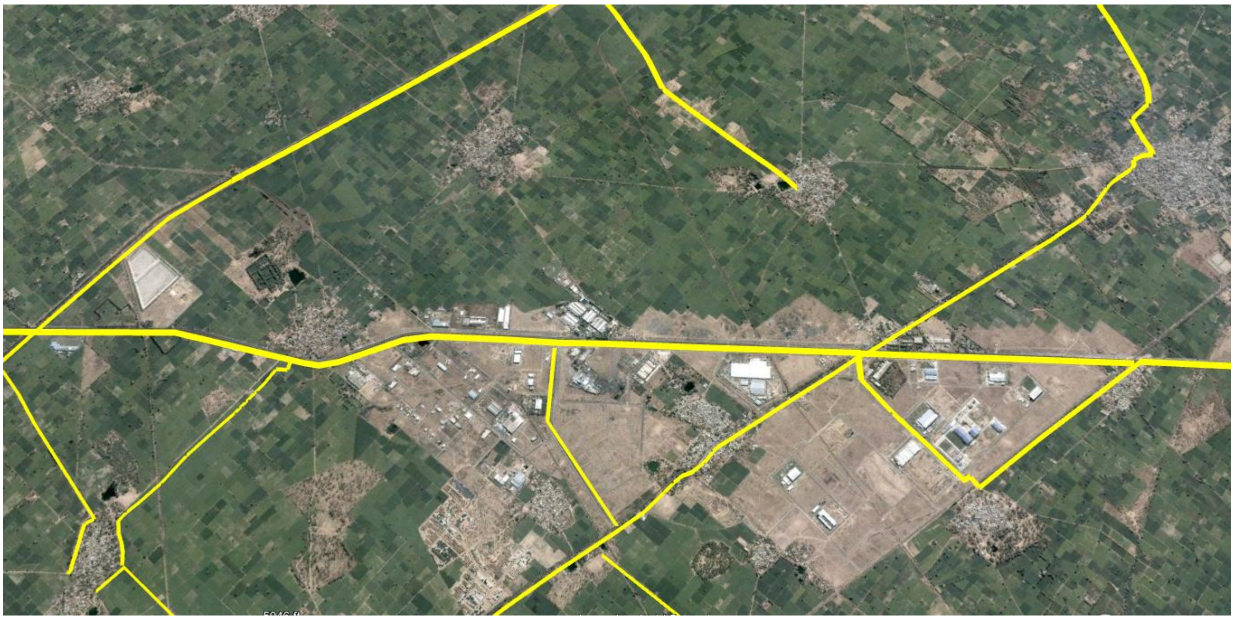

Figure2: The topographical Image of year 2006 of an Expressway (six – lane two way) in Deodhai village, district Rewari ,Haryana

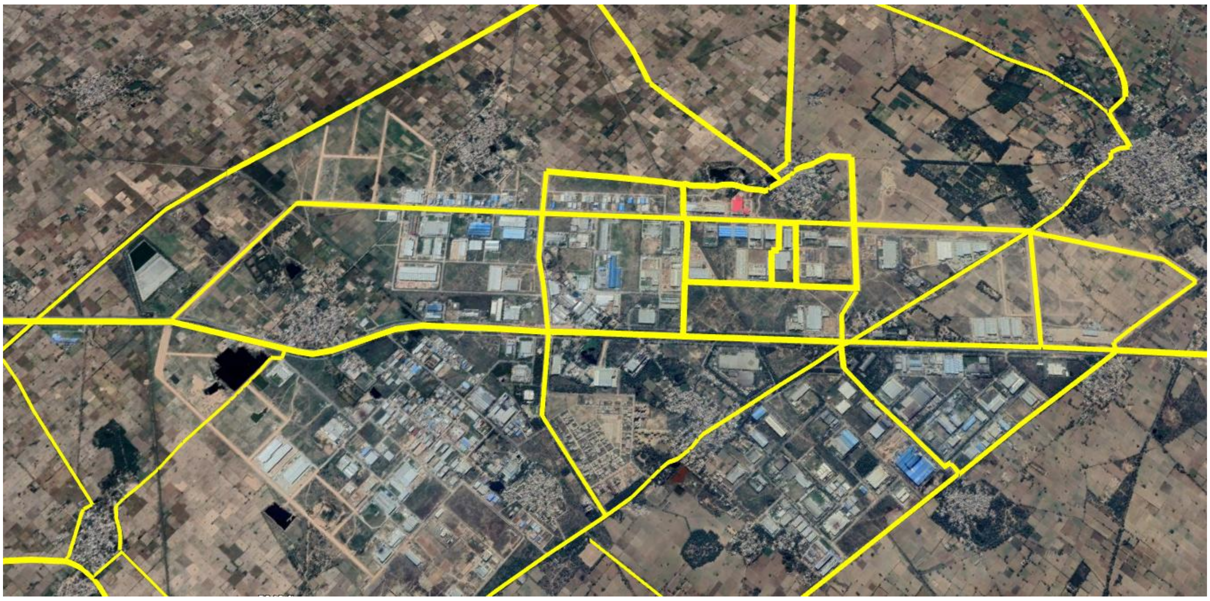

Figure3:The topographical Image of year 2014 (harvested season) Expressway (six-lane two way) in Deodhai village, district Rewari, Haryana of the year 2014

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Figure4: The topographical Image of year 2021 Expressway (six – lane two way) in Deodhai village, district Rewari , Haryana

5.2 Land Use land Cover at Deodhai village NH-48 Rewari district , Haryana

The following tables are shows the land use land cover in the period between 2006 to 2021 as shown below:

Table 2: Area Statistics of Rewari district of Haryana, the Year 2006

Land Use Land cover of Delhi - Jaipur Expressway NH-48 (2006)			
Sr. No	**LULC Class**	**Area (in square Km)**	**Area (in %)**
1	Agricultural Land	4615.32	61.03
2	Barren land	2625.64	34.72
3	Built up	109.65	1.45
4	Water Bodies	50.67	0.67
5	Roads	161.07	2.13
	Total	**7562.34**	**100**

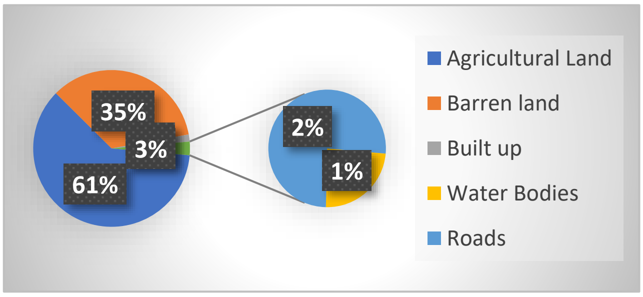

Figure 1: Pie Chart Showing land use land cover at Rewari district of Haryana NH-**48Year 2006**

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Table 3: Area Statistics of Rewari district of Haryana , Year 2014

Land Use Land cover of Delhi - Jaipur Expressway NH-48 (2014)			
Sr. No	**LULC Class**	**Area (in square Km)**	**Area (in %)**
1	Agricultural Land	4082.65	53.99
2	Barren land	2823.02	37.43
3	Built up	425.67	5.634
4	Water Bodies	42.34	0.56
5	Roads	174.70	2.31
	Total	**7562.34**	**100**

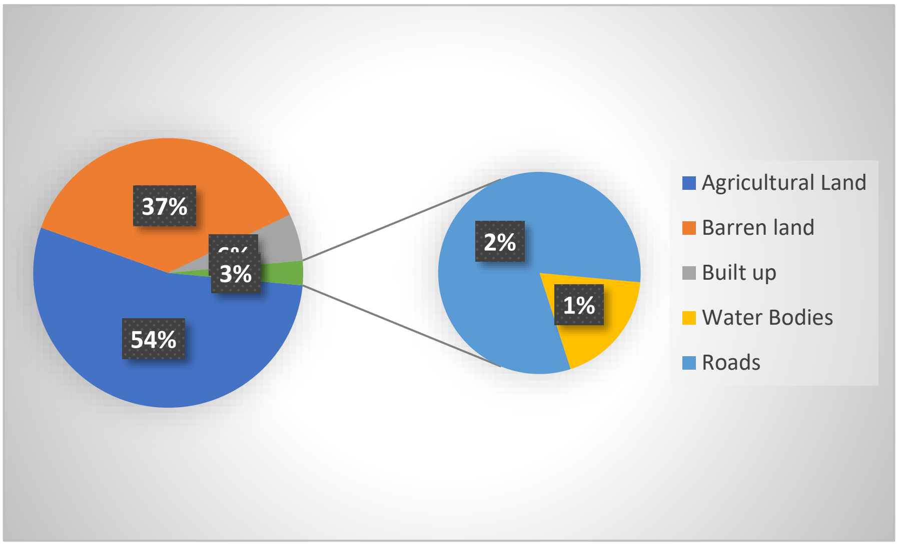


Figure 2: Pie Chart Showing land use land cover at Rewari district of Haryana NH-48 ,Year 2014

Table 4: Area Statistics of Rewari district of Haryana , Year 2021

Land Use Land cover of Delhi - Jaipur Expressway NH-48 (2021)			
Sr. No	**LULC Class**	**Area (in square Km)**	**Area (in %)**
1	Agricultural Land	3680.591	48.67
2	Barren land	1993.433	26.36
3	Built up	1362.734	18.02
4	Water Bodies	165.6152	2.19
5	Roads	359.9674	4.76
	Total	**7562.34**	**100**

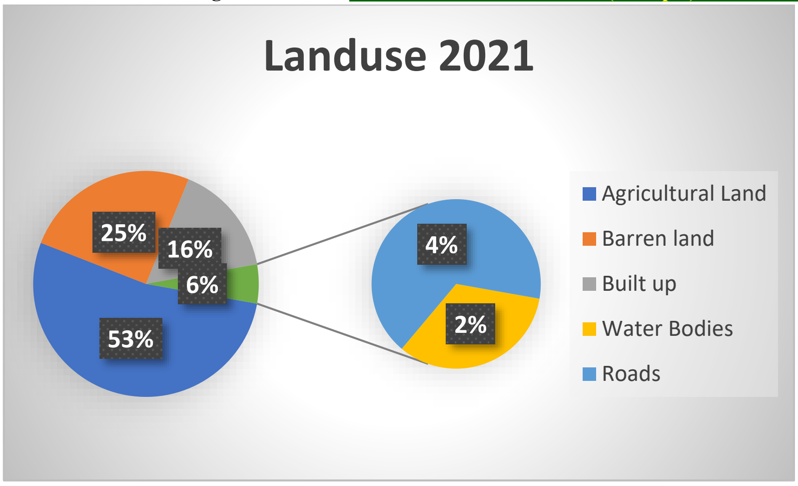


Figure 3: Pie Chart Showing land use land cover at Rewari district of Haryana NH-48 , the Year 2021

Table 4: Area statistics of NH-48 Rewari district of Haryana , Year 2006, 2014& 2021

Year	Land use (in %)				
	Agricultural Land	**Barren land**	**Built up**	**Water Bodies**	**Roads**
2006	61.03	34.72	1.45	0.67	2.13
2014	53.99	37.43	5.64	0.56	2.31
2021	48.67	28.67	18.02	2.09	4.73

5.3 Land use land Cover (LULC) Classification through ERDAS Software

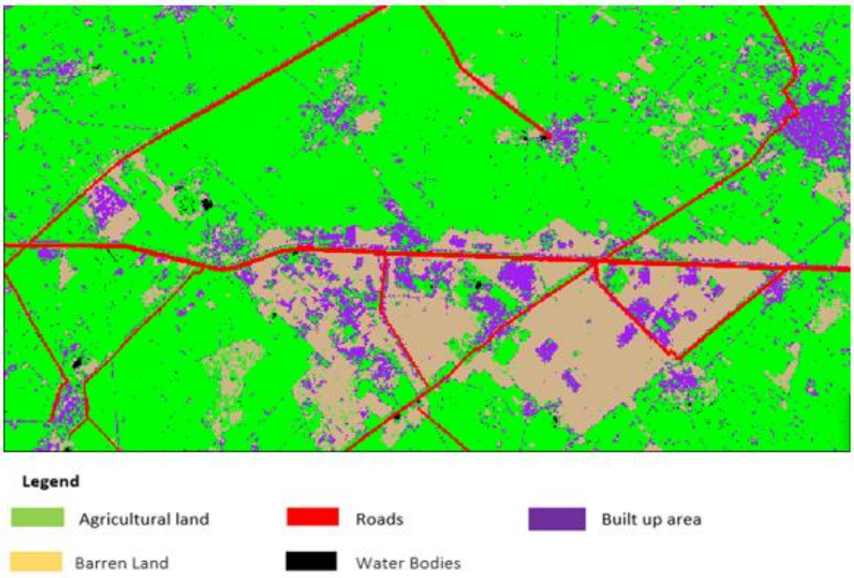


Figure 4: Land Use / Cover Map of Rewari District – NH48 Year 2006

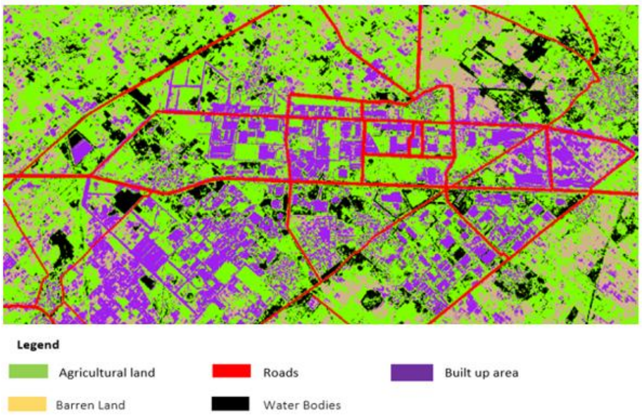


Figure 5 : Land Use / Cover Map of Rewari District – NH48 Year 2014

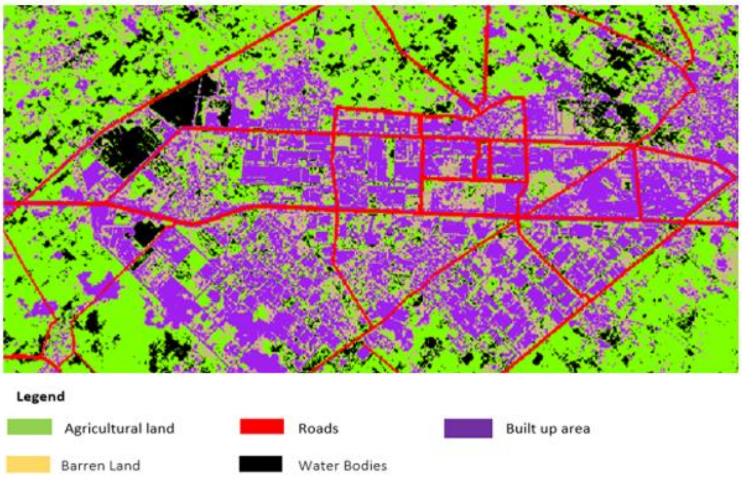
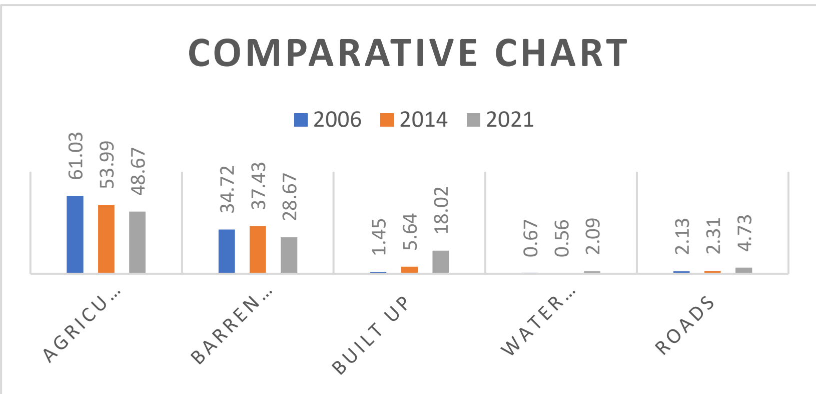


Figure 6: Land Use / Cover Map of Rewari District – NH48 Year 2021



2006 2014 2021 x-axis represents LULC classes

y-axis represents Area (in%)

Figure 7: Bar graph showing land use land cover at Rewari district of Haryana NH-48

5.4 Change Detection: Comparison between LULC Year 2006 to 2021

The following table shows the comparative study of the percentage of change that happened as :

Table5: Showing comparative percentage of land use and land cover of NH-48

Change detection at NH-48 between 2006 and 2021 (Area in %)				
SI no.	**LULC class**	**2006**	**2021**	**change**
1	Agricultural Land	61.03	48.67	-12.36
2	Barren land	34.72	28.67	-6.05
3	Built up	1.45	18.02	16.57
4	Water Bodies	0.67	2.09	1.42
5	road	2.13	4.73	2.6
	Total	**100**	**100**	

The expansion of infrastructure has resulted in a significant reduction of cultivated land; in 2006, agricultural land constituted 61.03%, but due to rapid development along the expressway, this figure is projected to decline to 48.67% by 2021. The settlement of infrastructure barren has also declined from 34.72% to 28.67%. The analysis indicates that the growth rate of the built-up area at the inception of the expressway was 0.85% in 2006, which subsequently escalated to 16.62% by 2021. During this era, road connectivity has improved from 2.13% in 2006 to 4.73% in 2021, enhancing the comfort of residents. To enhance comprehension, we have attempted to evaluate using graphs.

6. Conclusion:

The analysis indicates a reduction in agricultural and barren areas due to infrastructure development, which also demonstrates an enhancement in road connections for the mobility of individuals. The rate of infrastructure development along NH-48 accelerated more rapidly than in 2006. The data indicates that the proportion of developed land usage is increasing annually. Such Analysis helps predict the possible effect on land use patterns from the development of roads or infrastructure, and enables planners to decide on the rate of development without hampering the land use pattern of the area.

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