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RESEARCH ARTICLE

Application of Remote Sensing and GIS Techniques for Identification of Changes in Land Use and Land Cover (LULC): A Case Study

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Abstract

Objective: This study investigates the Spatial temporal changes of LULC in Mathura district of Uttar Pradesh, India, over the past 30 years (1990 to 2020). The study uses Landsat-5, Landsat-7 as well as Landsat-8 OLI images and GIS technique. **Methods:** The images are classified into LULC classes using a random forest classifier. The LULC changes are analyzed using a change detection analysis. The results of the change detection analysis were visualized using GIS. Confusion matrix is used for comparing the Crop classification during 1990–2020. User accuracy, consumer accuracy, producer accuracy, overall accuracy and kappa coefficient are used to compare the study of approximately three decades from 1990 to 2020. **Findings:** The classification of LULC is done into six classes i.e., urban, water bodies, vegetation, wheat, mustard and other crops. The results show that there are significant changes in LULC over the past 30 years. In the year 1990, 70.1 % accuracy and kappa 61.61 are obtained. In the year 2000, 70.8 % accuracy and kappa 63.02 are obtained. In the year 2010, 71.3% accuracy and kappa 64.8 is obtained. In the year 2020, 84% accuracy and kappa 80 are obtained. **Novelty:** In traditional mapping is not feasible, multi temporal satellite imagery can offer the crucial measurement of spatial and temporal phenomena for the research area. The study shows that the predominant land use in the area under investigation is vegetation. Less agricultural activity occurred between 2000 and 2010, which increased the amount of land covered by vegetation. The importance of monitoring LULC changes in order to understand the effects of these variations on the society as well as environment.

Keywords: Spatiotemporal changes; LULC; Landsat; GIS; agricultural expansion and urbanization

1 Introduction

A GIS (Geographic Information System) can be used to integrate and evaluate spatial data from several sources, making it an effective tool for crop classification. This can contain climate data, soil maps, aerial photos, and satellite information. Two effective methods that can be combined to categorize crops are geographic information systems (GIS) and remote sensing. Spatial data can be stored, analyzed, and visualized with the help of a GIS software system. Gathering information about the surface of the Earth from satellites or aircraft is known as remote sensing.

Land use and land cover (LULC) changes are a complex phenomenon that is influenced by a variety of factors, including population growth, economic development and climate change. LULC changes can have significant impacts on the environment, the economy, and human health. This study uses Landsat 8 OLI image to analyse the spatiotemporal changes of LULC in Mathura district from 1990 to 2020. Three Landsat sensors as Landsat-5, Landsat-7, and Landsat 8 OLI are used. These sensors provide high-resolution imagery that can be used to map LULC changes at a fine spatial scale. The study uses GIS techniques to analyse the LULC changes. GIS is a powerful tool that can be used to integrate spatial data, analyse spatial relationships and visualize spatial pattern, data on Mathura, Uttar Pradesh vegetation were extracted using remote sensing classification techniques from Landsat images taken in 1990 and 2020. A number of studies have been conducted on the spatio-temporal changes of LULC. These studies have used a variety of methods, including remote sensing, GIS, and statistical analysis.

One of the earliest studies on LULC change they used Landsat TM data to study the changes in LULC between 1980 and 1995. They found that the most significant changes were in the agricultural land, which had decreased by 10%. The urban area had also increased by 5%[1]. Another study has been used Landsat ETM+ data to find the changes in LULC between 1990 and 2005. They have found that the most significant changes were in the forest area, which had decreased by 15%. The agricultural land had also decreased by 5%. The urban area had increased by 10%[2]. A more recent study has been used Landsat 8 OLI data to study the changes in LULC between 2000 and 2017. They found that the most significant changes were in the urban area, which had increased by 20%. The agricultural land had also decreased by 5%. The forest area had remained relatively stable[3].

The study found that the district had experienced a significant increase in residential area, agricultural land as well as water bodies. The study also found that the district had experienced a decrease in forest cover[4]. Landsat 8 OLI images to analyses the spatiotemporal changes of LULC in Mathura district from 1990 to 2018. The district had experienced a significant increase in built-up area, agricultural land as well as water bodies. It also found that the district had experienced a Food production and the corresponding water use can be significantly impacted by the spatiotemporal variation of cultivated land[5]. Historical information about soils, populations, climatic factors, and terrain is employed. Using a variety of sophisticated geographic methods datasets were advanced to set of 30 m grid cells used for allocation models as well as agriculture land. In it reconstructions of the spatiotemporal spreading of agricultural area in Nepal shows an upward trend (from 151.2 102 km^2 to 438.8 102 km^2) between 1910 and 2010[6].

Data on Malaysian forests were extracted using remote sensing classification techniques from Landsat photos taken in 1990 and 2017. Analysis was done on the spatial-temporal changes that occurred in agricultural lands as well as Malaysia's forests among 1990 and 2017. The findings revealed a 441 Mha, or 21%, decline in Malaysia's natural forests[7]. Author suggested quantity variations in land use in a case study area in Iran, Chalous and to pinpoint the geophysical (such as elevation, slope and soil) and socioeconomic (such as population density, accessibility, the tourism sector and land price) components of such variations. For 1996, 2006, and 2016, respectively, supervised classification founded on the maximum likelihood classifier was used to generate land use classes. Additionally, a change detection investigation revealed that over a 20-year period, built-up areas expanded by 15.89% while agricultural land decreased by 11.09%[8]. Spatially explicit agricultural area, soil types. Statistical data, population density and climate and topography variables were all taken. The data that was available and updated it based on a spatiotemporal reform of agricultural LULC. For models of agricultural land suitability and allocation, 30*30 m grid cells were the foundation for the various datasets. Between 1970 and 2010, the historical farming area reform showed an increase in agricultural land, from 37.03 to 43.88[9].

A few instances of how LULC modifications may impact a community, its residents, and the environment:

- Soil erosion, climate change, and biodiversity loss are all consequences of deforestation.
- Increased air and water pollution, traffic congestion, and the urban heat island effect are some of the negative effects of urbanization that can affect people's ability to support themselves and their families who rely on forests for food, medicine, and other resources.
- The loss of agricultural land, water contamination, and soil salinization are all consequences of agricultural development, which can also force people from their homes and communities. Additionally, it can negatively affect rural livelihoods and food security.

Changes in Land Use and Land Cover (LULC) can have distinct effects for certain locations and populations, in addition to these broader ones. Deforestation in the Amazon rainforest, for example, may result in higher emissions of greenhouse gases, which fuel global warming. Coastal cities may become more susceptible to flooding and sea level rise as a result of urbanization. Increased agricultural production in arid areas may result in a shortage of water.

To comprehend the effects of LULC changes on society and the environment, it is critical to track these changes. With this data, policies and management plans can be created to lessen the negative effects of LULC changes and advance sustainable development.

Some particular instances of how LULC modifications have impacted various areas and demographic groups:

- Millions of hectares of forest have been lost due to deforestation in the Amazon rainforest, which has had a disastrous effect on biodiversity.
- Urbanization has increased flooding and sea level rise in coastal cities worldwide. Trees absorb carbon dioxide from the atmosphere, which has contributed to climate change. This is due to the fact that cities are frequently constructed on low-lying terrain and have a large number of impermeable surfaces that stop water from penetrating the earth. Water scarcity has resulted from agricultural expansion in dry regions. This is because there isn't enough water in arid areas to supply all of the needs, and agriculture takes a lot of water.

It is crucial to remember that the effects of land use and conservation (LULC) changes are multifaceted and contingent on various elements, including the kind, extent, and location of the changes. On the other hand, it is evident that LULC modifications can have a big effect on the environment and society. We can better comprehend the ramifications of LULC changes and create plans to lessen their adverse effects and advance sustainable development by keeping an eye on these changes.

1.1 Scope of the study

An essential component of an advanced organization is data. In the state of Uttar Pradesh, a method is introduced. Data on metropolitan areas, bodies of water, vegetation, and crops from 1990 to 2020 year were needed for this technique. The Indian agricultural website was utilized to compile district-specific crop data. As a categorical variable, the yield is being forecasted using classification models. The three factors that most affect crop productivity are crop type, season, and region. Crop production categorization models are found by fitting training datasets with pre-processed restrictions.

In order to minimize the error between the real and predicted values during model training, we used Google Earth Engine to create the classification models. Many machine learning techniques that are good at classification have been used, including Random Forest (RF).

1.2 Problems

Some of the challenges are face during this work:

- Selecting the right dataset and pre-processing the data are more preferable in order to achieve a better result.

- Reduced processing power consumption in the training of classification models.
- Increased mistake rate as a result of the districts' dynamic environment.

One of the main difficulties with this research is taking images in the overcast weather. Not much less than 10% of the cloudy weather is significant. In the past years, crop classification techniques have become more complex, expensive, and time-consuming. Reliable and ideal crop classification is required for food security, ranging from territorial to global, and these are the primary goals of this research. The generation of crop classification presents a "Big Data" challenge due to the increased availability of satellite imagery. Many people are interested in using RF, Decision Tree, Logistic Regression, and Artificial Neural Network for crop categorization across large areas.

Thus, spatial temporal changes utilizing a variety of methodologies. The following are the contributions.

- To examine how well multi-spectral information from the Landsat-8 OLI satellite can be used to categorize different classes using the RF approaches.
- Several supervised machine learning classifiers, such as Random Forest (RF) are tried in order to create a confusion matrix and graph of the dataset.
- The best overall classification accuracy was achieved by the Landsat 8 OLI image using RF method is 84% in 2020 year.
- Cropland (wheat, mustard and other crops) has increased by 10%, while vegetation has decreased by 20%. While water bodies have increased by 5%. Urban areas have increased by 50%, and barren land has increased by 15%.

Additionally, work makes a substantial contribution to the assessment of the use of RF approaches for six classes. Also predict spatial temporal change over past 30 years. It helps to predict misclassified pixel into other classes. Additionally, help to find out the area of classes. The study also highlighted the importance of monitoring LULC changes in order to recognize the impacts of these variations on the society as well as environment.

The study was conducted with the following goals

- Creating LULC maps for various time periods
- figuring out the rate of change for various LULC classes from 1990 to 2020
- LULC change preparation based on completed study.

Table 1 shows related study of LULC for various years.

Table 1. Related Literature Survey

Ref. No	Author, year	Location	Methods	LULC time period	Result
[10]	Mariye M et al. 2022	Doyogena district, southern Ethiopia	Maximum likelihood	1986–2020	The outcome revealed that the amount of forestland had significantly decreased, from 1756.7 ha (38.8%) in 1973 to 71.6 ha (1.6%) in 2020. During the previous 35 years, wetlands have decreased progressively, falling from 16.8 ha/year in 2000–2010 to 6.3 ha/year in 1986–2020, respectively.
[11]	Jane Ferah Gondwe et al. 2021	Blantyre City	Artificial neural network	1999-2019	According to the study, the areas of built-up and agricultural land rose by 28.54 km^2 (194.81%) and 35.80 km^2 (27.16%), respectively, with corresponding annual change rates of 1.43 km^2/year−1 and 1.79 km^2/year−1. Bare land, forested land, herbaceous land and waterbody areas had decreases of 0.05%, 90.52%, 71.67%, and 6.90%, in that order.

Continued on next page

Table 1 continued

[12]	Rahman, Md et al. 2021	Bangladesh City	Maximum likelihood classification (MLC)	1990-2020	Cropland, barren land, waterbody, and wetlands have all declined between 1990 and 2020 by 30.63%, 11.26%, 23.54%, and 21.89%, in that order. Concurrently, there has been an increase of 161.16% in the built-up area and 5.77% in the vegetation.
[13]	Pawan kumar et al. 2021	Jhansi City	MLC	2000-2020	The findings indicated that whereas fallow/barren land and forest had reduced by 27.55% (1386.58 Km^2) and 0.5% (25.34 Km^2), respectively, crop land, built-up area, and water bodies had expanded by 27.16% (1367.26 Km^2), 0.58% (29.4 Km^2), and 0.3% (15.26 Km^2). According to the research, there has been a significant conversion of fallow/barren land (27.55%) to crop land.
[14]	Mohammad Arif et al. 2023	Burdwan city	Supervised Classification	1987–2002 and 2002–2017	The share of built-up land has expanded by 182.8%, while that of vegetation and water bodies has dropped by 72.3% and 56.3%, respectively, according to the results. A built-up pattern that mostly pointed north-west, north, north-east, and south-east was also discovered by the research.

The study demonstrates the necessity for policymakers and other stakeholders in the area to be aware of Bhaluka's rapid development and shifting land use patterns. As a result, it is concluded that a significant shift in LULC has occurred, with the last 20 years being mostly attributed to the acceleration of industrialization and urbanization in the studied area [15].

The purpose of this study is to determine whether changes in PM2.5 concentration are related to LULC characteristics. [16]

2 Methodology

2.1 Study Area

Mathura is a holy city in Uttar Pradesh, India that is home to the Krishna Janma bhoomi temple complex. The city has undergone significant LULC changes in recent decades, due to a number of factors including urbanization, industrialization, and agricultural expansion. The latitude as well as longitude of Mathura is 27.4924° N and 77.6737°E. The district has a population of over 2.5 million people ((Census Report 2011)), (State of Forest Report 2020, mathura.kvk4). Total geographical area is 3.32 mha and total cultivation land 3.28 mha and total irrigated land is 3.11mha. It is a large cultivation area. Crops are sown according to the seasons. There are two seasons Rabi and Kharif in which crops are sown. Mainly two crops are highly sown which are Wheat and Mustard in Mathura at winter (Rabi) season (Mathura District Census Report 2011). Figure 1 shows study area of this research.

This study uses Landsat-5, 7, and 8 OLI (USGS) images to analyze LULC changes in Mathura from 1990 to 2020. The results of the study show that there has been a significant increase in the area of urban land, as well as a decrease in the area of cropland and water bodies. The study also found that there has been an increase in the area of barren land, which is likely due to soil degradation and deforestation (Mathura District Water Resources Management Plan 2020-2030).

Urban areas: The urban area of Mathura has expanded significantly over the past 30 years. In 1990, the urban area covered an area of approximately 20 square kilometers. By 2020, the urban area had expanded to over 100 square kilometres. This expansion is due to a number of factors, including population growth, economic development, and religious tourism.

Agriculture (Crops): The agricultural area of Mathura has declined slightly over the past 30 years. In 1990, the agricultural area covered an area of approximately 500 square kilometers. By 2020, the agricultural area had declined to approximately 450 square kilometers. This decline is due to a number of factors, including urbanization, industrialization, and water scarcity.

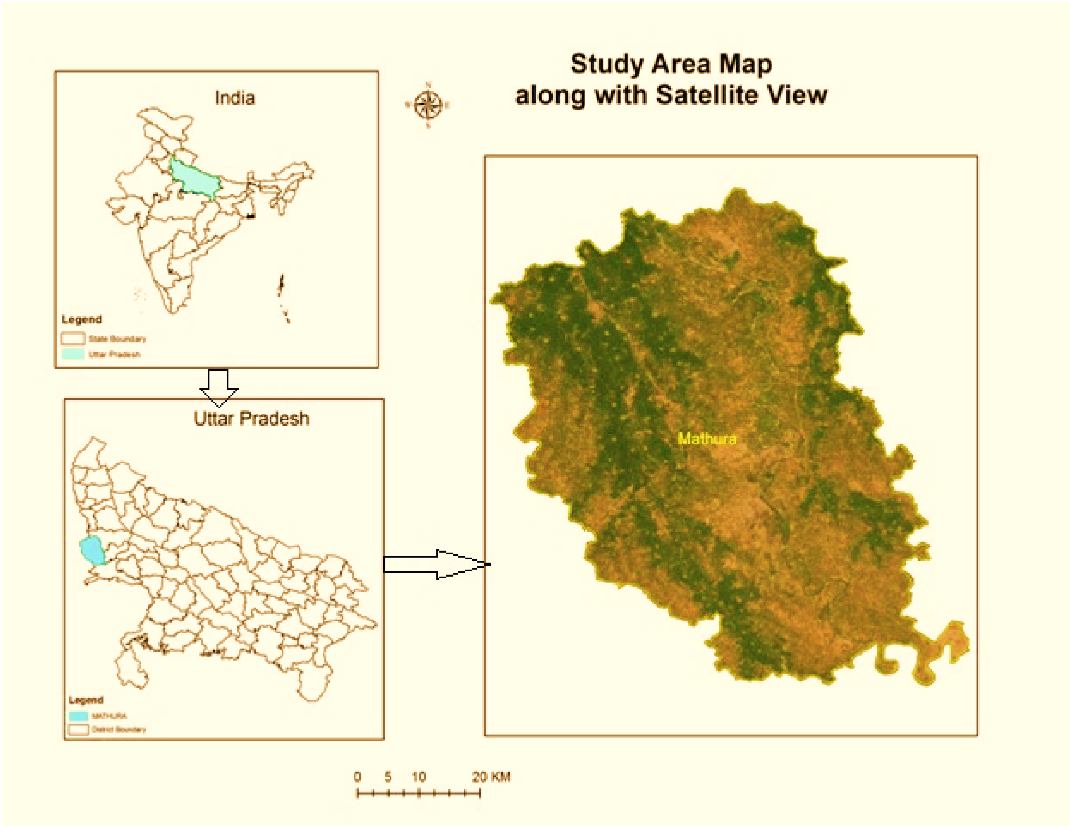


Fig 1. Study area Map

Vegetation: The forest area of Mathura has remained relatively stable over the past 30 years. In 1990, the forest area covered an area of approximately 100 square kilometers. By 2020, the forest area had remained at approximately 100 square kilometers. This stability is due to the efforts of the government to protect the forests in the region.

Water bodies: The area of water bodies in Mathura has declined slightly over the past 30 years. In 1990, the area of water bodies covered an area of approximately 50 square kilometers. By 2020, the area of water bodies had declined to approximately 45 square kilometers. This decline is due to a number of factors, including urbanization, industrialization, and water pollution (https://mathura.kvk4.in/district-profile.php). Table 2 describes supervised land classes used in this research classified by random forest method.

Table 2. Supervised Land Classes by Random Forest method

Classes	Land Classes	Description
0	Urban	Built up area, Home, Factories
1	Water	Cannel, River, Water body
2	Vegetation	Forest, Tree
3	Wheat	Wheat Crops
4	Mustard	Mustard Crops
5	Other Crops	Paddy rice (Dhaan), Maize , Cotton, Bajra, Jawar

Table 3 describes remote sensing image that is used in research. The spatio-temporal changes of LULC in Mathura district have had a number of environmental, social, and economic impacts. The expansion of the urban area has led to increased pollution, traffic congestion and the loss of agricultural land. The decline of the agricultural area has led to increased food insecurity and the loss of biodiversity. The decline of the forest area has led to increased soil erosion and the loss of watershed functions. The spatio-temporal changes of LULC in Mathura district are a complex issue with a number of contributing factors.

Table 3. Remote sensing images used in this paper

Year	Satellite & Sensors	Date Acquisition	Resolution (m)
1990	Landsat 5 TM	1990-12-01 to 1991-01-30	30
2000	Landsat 7 TM	2000-12-01 to 2001-01-30	30
2010	Landsat 7 TM	2010-12-01 to 2011-01-30	30
2020	Landsat 8 OLI	2020-12-26 to 2020-12-30	15

The government and the local community need to work together to develop a sustainable land use plan for the region. This plan should aim to protect the environment, meet the needs of the growing population, and promote economic development [17–20].

2.2 Method

The study area is located in Mathura district, Uttar Pradesh, India. The study area is approximately 1000 square kilometres in size. The Landsat-5, 7, and 8 OLI images were obtained from the United States Geological Survey (USGS). The images were processed using the Arc GIS software package. Landsat-5, 7 and 8 OLI data are used to classify LULC in Mathura district from 1990 to 2020. The data are pre-processed to remove cloud cover and other artefacts. The images were then classified using a supervised classification approach. The following land cover classes were used: Urban or built-up land, Cropland (wheat, mustard and other crops) Water bodies and vegetation. The LULC classification is performed using the random forest supervised classification method. The training samples are collected from the satellite and from Google Earth images. The study uses three Landsat sensors as Landsat-5, Landsat-7 and Landsat 8 OLI. These sensors provide high-resolution imagery that can be used to map LULC changes at a fine spatial scale. The study used GIS techniques to analyse the LULC changes. GIS is a powerful tool that can be used to integrate spatial data, analyse spatial relationships and visualize spatial patterns. The study used the following steps to analyse the LULC changes:

- The Landsat images are pre-processed to remove atmospheric effects and geometric distortions.
- The images were classified into LULC classes using a supervised classification approach.
- The LULC changes are analysed using a change detection analysis.
- The results of the change detection analysis are visualized using GIS.

3 Results and Discussion

Section 3 describes result and discussion. Comparative study table are used to describe various outcome of LULC with different methods. To look into trends of land usage and assist in predicting future sustainable land management, LULC is essential. In this section outcome is observed. The study found that the Mathura district had experienced significant LULC changes over the past 30 years. The main LULC changes were: an increase in built-up area, agricultural land, decrease in water bodies and a forest cover. Table 4 shows comparative study of LULC change detection.

Table 4. Comparative Study of LULC Change detection

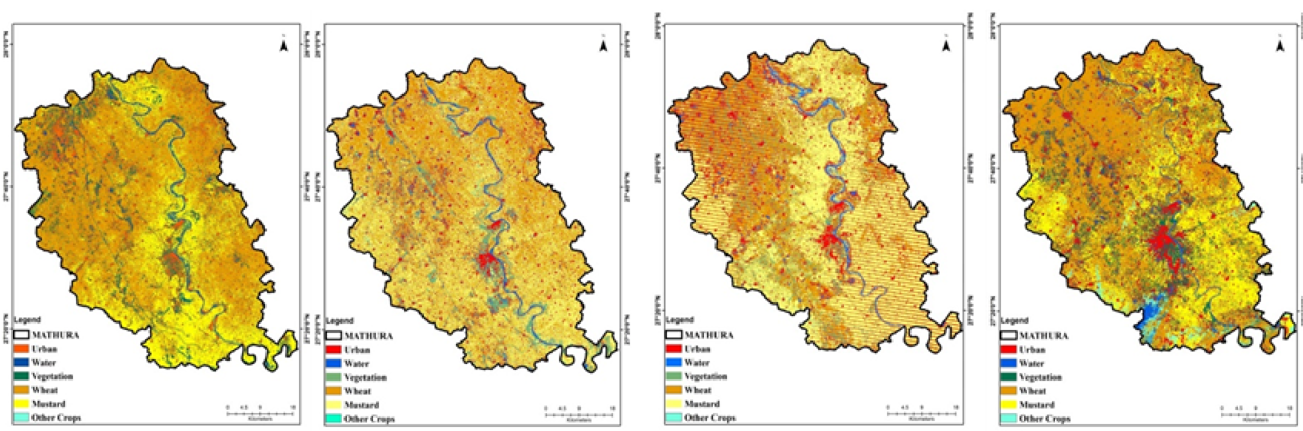
Ref. No.	Authors	Classification Techniques	Overall Accuracy and Kappa Coefficient	Result
(21)	Jian Cui et al. 2023	RF	92.08, 0.90	The share of development land climbed from 16.73% to 29.54%, while the proportion of agricultural declined by 1.75%.
(8)	Zohreh Alijani et al. 2020	MLA	93.50%, 0.89	It revealed that over a 20-year period, built-up areas expanded by 15.89% while agricultural land decreased by 11.09%.
(7)	Jinfeng Yan et al. 2020	The classification method of knowledge rule set	-	The findings demonstrated a 21% decline in Malaysia's natural forests, or 441 Mha.

Continued on next page

Table 4 continued

(22)	XueWang et al. 2020	China AEZ model	-	The findings showed that the area under cultivation expanded by 1.62% between 1990 and 2000 and then steadily declined between 2000 and 2015, culminating in a 0.80% rise in the total area under cultivation at the national level between 1990 and 2015.
(23)	Zadbagher et al. 2018	Object based classification	77%	Future loss was predicted using the Markov chain model for cellular automata.
(24)	Choudhary et al. 2018	MLC	-	This study encounters shifts in vulnerability and LULC.
(25)	Saleem et al. 2018	MLC	89%, 0.86	Economic, demographic, and urbanization expansion at a rapid pace
(26)	Prabu and Dar et al. 2018	MLC	86.15%	Because of human settlement, the city's LULC patterns have rapidly changed.

The study also found that the LULC changes were not evenly distributed across the district. The built-up area had increased most rapidly in the urban areas, while the agricultural land had increased most rapidly in the rural areas. In 1990 year, obtained 70.1 % accuracy and kappa 61.61. In 2000 year, we obtained 70.8 % accuracy and kappa 63.02. In 2010 year, obtained 71.3% accuracy and kappa 64.8. In 2020 year, obtained 84% accuracy and kappa 80. Confusion matrix is used to analyze the performance. With the help of confusion matrix, we calculated user accuracy, producer accuracy and consumer accuracy and is shown in Table 5. User accuracy and producer accuracy are two metrics used to assess the accuracy of a land cover classification map. User accuracy is the proportion of pixels that are correctly classified as the ground truth class. If a map has a user accuracy of 80% for the "water" class, then 80% of the pixels that are classified as "water" are actually water. Producer accuracy is the proportion of pixels that are correctly classified as the ground truth class, given that they are actually that class. In other words, user accuracy measures how well the map matches the ground truth, while producer accuracy measures how well the map classifies the ground truth. Classified crop maps are shown in Figure 2 (a) to (d). Figure 3 shows post classification from 1990 to 2020.



(a) 1900 (b) 2000 (c) 2010 (d) 2020

Fig 2. Classification Map using Random Forest Method

Table 5. Confusion matrix (%) comparing the Crop classification of 1990–2020 using Random Forest Classifier

Year	Classes	Urban (0)	Water (1)	Vegetation (2)	Wheat (3)	Mustard (4)	Other Crops (5)	Total	User Accuracy (%)
1990	Urban (0)	383	0	4	5	8	0	400	95.75
	Water (1)	8	106	3	2	3	0	122	86.88
	Vegetation (2)	18	5	246	7	10	0	286	86.01
	Wheat (3)	19	2	9	367	6	0	403	91.06
	Mustard (4)	4	2	3	23	367	0	399	91.97
	Other Crops (5)	0	0	2	10	7	34	53	64.15
	Total	432	115	267	414	401	34	1663	
	Producer's Accuracy (%)	86.5	57.5	59.2	66.2	70.4	33.3	-	
	Consumer's Accuracy (%)	88.6	92.1	92.1	88.6	91.5	100		
	Overall Accuracy	70.1							Kappa 61.61%
2000	Urban (0)	390	0	3	4	4	0	401	97.25
	Water (1)	4	120	2	1	0	0	127	94.48
	Vegetation (2)	7	1	278	0	3	0	289	96.19
	Wheat (3)	3	1	4	361	9	0	378	95.50
	Mustard (4)	3	2	7	22	358	0	392	91.32
	Other Crops (5)	1	0	6	4	4	34	49	69.38
	Total	408	124	300	392	378	34	1636	
	Producer's Accuracy (%)	93.51	53.8	69.2	73.9	64.2	17.6	-	
	Consumer's Accuracy (%)	93.3	97.2	95.6	91.5	92.9	100		
	Overall Accuracy	70.8							Kappa 63.02%
2010	Urban (0)	396	0	1	0	3	0	400	99
	Water (1)	5	104	5	3	0	0	117	88.88
	Vegetation (2)	11	2	232	5	4	0	254	91.33
	Wheat (3)	13	4	12	312	8	0	349	89.39
	Mustard (4)	8	2	0	6	352	0	368	95.65
	Other Crops (5)	1	0	4	4	5	39	53	73.58
	Total	434	112	254	330	372	39	1541	
	Producer's Accuracy (%)	78.3	70.3	55	65	80.6	18.1	-	
	Consumer's Accuracy (%)	90.5	95.5	90	93.2	96.4	97.2		
	Overall Accuracy	71.3							Kappa 64.8
2020	Urban (0)	386	0	2	2	1	0	391	98.72
	Water (1)	3	113	2	1	1	0	120	94.16
	Vegetation (2)	3	1	258	4	2	0	268	96.26
	Wheat (3)	7	0	0	381	1	0	389	97.94
	Mustard (4)	0	0	0	2	397	0	399	99.49
	Other Crops (5)	0	0	2	4	3	44	53	83.01
	Total	399	114	264	394	405	44	1620	
	Producer's Accuracy (%)	91	74	80	82	92	33	-	
	Consumer's Accuracy (%)	96	99	97	96	98	1		
	Overall Accuracy	84							Kappa 80%

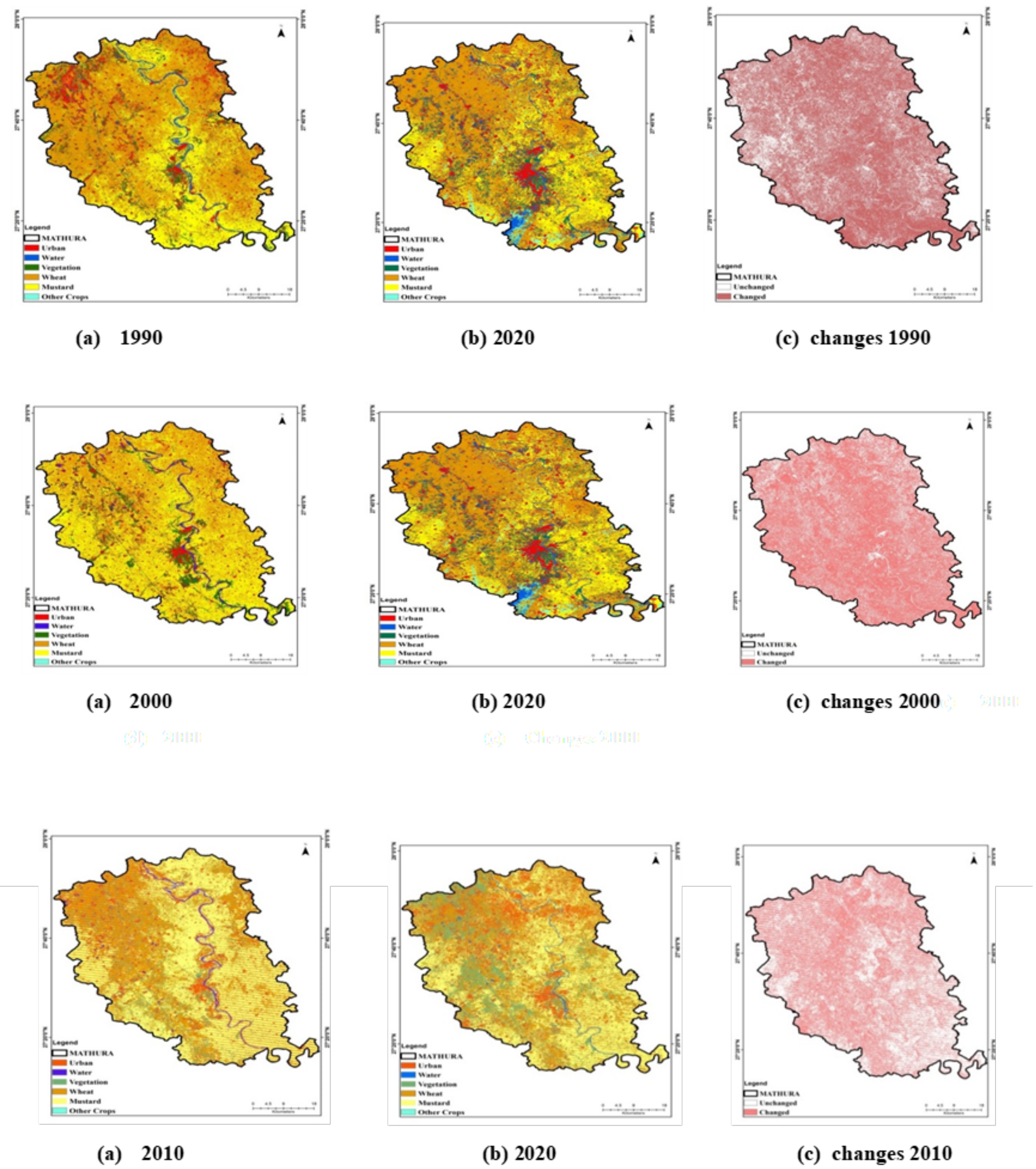


Fig 3. Post Classification from 1990 to 2020

3.1 Accuracy Assessment

$$Accuracy = \frac{(Tpp + Tnn)}{(Tpp + Tnn + Fpp + Fnn)} \quad (1)$$

Where Tpp represents True positive, Tnn represents True negative, Fpp represents False positive and Fnn represents False negative.

$$Overall\ accuracy = \frac{sum\ of\ diagonal\ element}{Total\ number\ of\ samples} * 100 \quad (2)$$

A statistical test to evaluate an accuracy of classification yields the kappa. Kappa essentially the categorization outdone simply randomly assigning values, whether it achieved enhanced than random.

$$Kappa = \frac{(observed\ correct - \ expected\ correct)}{(1 - \ expected\ correct)} \tag{3}$$

Where observe correct, denotes accuracy reported in overall accuracy and expected correct represents correct classification (egyankosh.ac.in/bitstream/123456789/39544/1/Unit-14.pdf).

The results showed that there is a significant increase in the area of urban as well as built-up land, as well as a decrease in the area of water bodies. The main drivers of LULC change were population growth, economic development, and agricultural intensification. The area of urban and built-up land increased from 234.45 km^2 in 1990 to 332.16 km^2 in 2020. The area of water bodies decreased from 40.49 km^2 in 1990 to 36.31 km^2 in 2020. The results of the LULC classification show that there has been a significant increase in the area of urban land in Mathura from 1990 to 2020. The area of urban land increased from 234.45 km^2 in 1990 to 332.16 km^2 in 2020. The area of cropland decreased from 1051.61 km^2 in 1990 to 681.77 km^2 in 2020. The area of water bodies decreased from 40.49 km^2 in 1990 to 36.31 km^2 in 2020. The area of barren land increased from 983.07 km^2 in 1990 to 1108.59 km^2 in 2020. Table 6 shows total pixel converted from one class to other class. Table 7 shows area cover by classes.

Table 6. Pixel changes from one class to other

S.NO	Classes	Pixels change	classes	Pixels change
1	101	200	401	257
2	102	56	402	144
3	103	137	403	371
4	104	105	404	189
5	105	8	405	20
6	201	19	501	471
7	202	21	502	164
8	203	17	503	566
9	204	5	504	228
10	205	1	505	24
11	301	116	601	10
12	302	35	602	6
13	303	93	603	13
14	304	54	604	7
15	305	5	605	1

Table 7. Area of classes

S.NO	classes	Area	classes	Area
1	101	2162848	401	3108324
2	102	743346.9	402	1995810
3	103	1506143	403	4240789
4	104	1195368	404	2192934
5	105	86913.74	405	229522.1
6	201	229448.3	501	4776447
7	202	279156.9	502	2134664
8	203	211094.8	503	5801917
9	204	64052.33	504	2463109
10	205	7134.57	505	232940
11	301	1377605	601	91121.96
12	302	527637.9	602	74540.4
13	303	1193890	603	123545.7
14	304	667812.1	604	77489.65
15	305	55281.96	605	6001

4 Discussion

The study findings suggest that the Mathura district is undergoing rapid LULC changes. These changes are being driven by a number of factors, including population growth, economic development, and climate change. The LULC changes in Mathura district have a number of implications for the environment, the economy, and human health. The increase in built-up area is leading to habitat loss and fragmentation for wildlife. The decrease in forest cover is leading to a decrease in air quality and an increase in the risk of flooding. The results of this study showed that LULC changes in Mathura district are having a negative impact on the environment. The increase in urban and built-up land is leading to increased pollution and decreased biodiversity. The decrease in cropland is leading to increased food insecurity. The decrease in water bodies is leading to increased water scarcity. There is a need for better planning and management of land resources in Mathura district in order to mitigate the negative impacts of LULC change. This could include measures such as promoting sustainable land use practices, improving waste management, and conserving water resources. In[8] used only 20 years' changes detection from 1996 -2016. This study involved changes detection 30 years from 1990 to 2020. In[7] used classification method of knowledge rule set for change detection. This study was only focused on changes analysis, no performance matrix as accuracy and kappa not calculated. This purposed study also focuses on changes analysis as well as performance parameters and mixed pixel classes with other classes. For classification study used Random method. It based on ensemble concepts, that gives good prediction as compared to others. This technique has not yet been utilized in this field. This is a recent work in this field and time frame. The results give Mathura city authorities knowledge about driving causes and changes in LULC that they can use to create plans for sustainable development. These obstacles are mostly caused by the region's complex vegetation, slope and mountainous topography, and unfavorable climate. This is why it was so difficult to locate satellite images that are usable and clear. In addition, there were other issues that arose from the use of distinct sensor technologies (spectral and spatial resolution) when comparing Landsat TM and OLI data and determining land cover. By independently applying the supervised classification change detection technique to both images, an attempt was made to solve these issues.

5 Conclusion

This study investigates LULC changes in Mathura district, Uttar Pradesh, India from 1990 to 2020 using Landsat-5, 7 and 8 OLI data and GIS techniques. It analyzes the spatiotemporal changes of LULC over the past 30 years. The results show that there is a significant increase in the area of urban and built-up land, as well as a decrease cropland and water bodies. The main drivers of LULC change are population growth, economic development and agricultural intensification. The study concluded that LULC changes are having a negative impact on the environment and that there is a need for better planning and management of land resources in the future. The research area's LULC changes are ascribed to factors such as population growth, urbanization, social-economic expansion, and climate change.

The resolution of the satellite data used in this study is 30 meters. It is not the best option for in-depth research, but it might be suitable for small-scale projects. The investigation must be conducted using free, medium-quality Landsat images because higher-resolution images are costlier. It affected the accuracy in certain ways. The greatest amount of urban green space is visible during the rainy season because the leaves appear greener than they do throughout the winter. Nevertheless, it was hard to locate anticipated data from the wet season because of the dismal weather. Rather, the data was collected in December and January. Sometimes developed regions are disregarded because they are shaded by the forest canopy. Small-scale green spaces cannot be examined due to the 30 m pixel size limit, as a result, many rooftop gardens or roadside plants may have been overlooked from the research, leading to errors. These were the restrictions on the study.

For Future we can extend this work in other area and add some more classifiers. Compare many datasets in the future to spot trends and make predictions about the future.

Author Contributions

Priyanka Gupta: conceptualization, data set curation, methodology, formal analysis; Prateek Gupta: formal analysis, visualization, investigation. Suraj Kumar Singh: formal analysis, visualization. & Varun Narayan Mishra: formal analysis, Shruti Kanga: validation. All the authors have read as well as agreed to the publish version of the manuscript.

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