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LAND USE LAND COVER CHANGE ASSESSMENT IN FATEHABAD DISTRICT, HARYANA: A GIS AND REMOTE SENSING BASED CASE STUDY

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SUMMARY

The Land Use Land Cover (LULC) information has always played a significant role in planning, management, and monitoring of various programmes at local, regional, and national levels. Changes in LULC are the direct and indirect consequences of human and climatic actions happened in that region. An attempt has made to study the changes in LULC pattern of Fatehabad district in the Haryana, India for the period of year 2016 and year 2021 using the Remote Sensing and Geographic Information Systems (GIS). The Sentinel 2A, MSI data and supervised classification using maximum likelihood supervised classifier was used to prepare the land cover maps of the district. The five main LULC classes *viz*; water bodies, built-up, fallow, Agriculture and vegetation have undergone significant changes in last five years. The present study is focused on the land use and cover change detection with a total covering an area of 2,538 sq. km of the district. The increased in built-up area from year 2016 to year 2021 has indicated the expansion in urbanisation, increased population and industrial activities in the district. The decreased in water bodies area by 27.21%, vegetation by 44.22%, and increase in fallow land by 16.41% present an alarming situation from 2016 to year 2021. However, in further studies the inclusion of other co-variable which contributes in LULC changes in the analysis should certainly improve the results of the study.

Key words: Change detection, classification, land use land cover, remote sensing

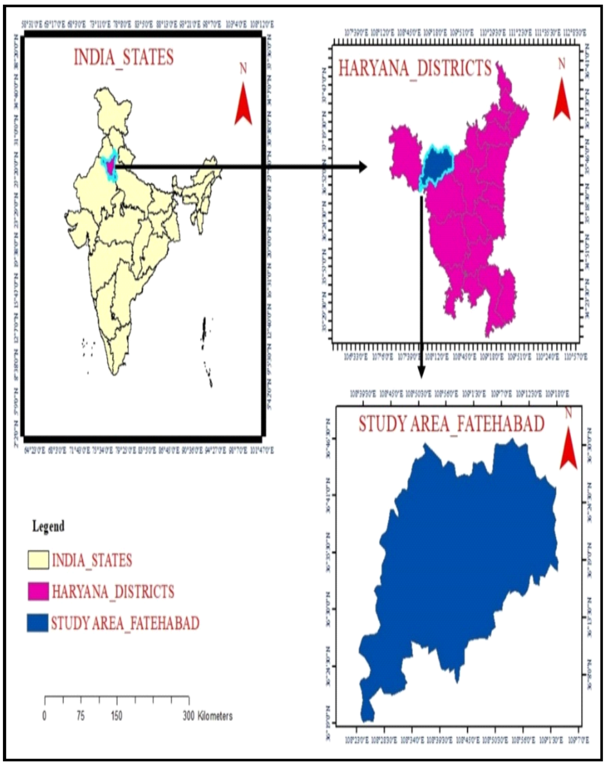
At local, regional, and global levels, humans have been transforming land to get food and other necessities for survival. Controlling the negative effects of LULC changes while maintaining the production of key resources has become a major focus of researchers and institutions around the world. Although the phrases "land use" and "land cover" are frequently used interchangeably, each term has a distinct meaning. Land cover refers to the flora, urban infrastructure, water, and bare soil that cover the earth. Land cover identification provides the foundation for operations such as thematic mapping and change detection analysis. Land use describes the function of a piece of land, such as recreation, wildlife habitat, or agriculture. Remote sensing technology has advanced at a breakneck pace. Satellite images are now being acquired. Access to data has never been higher, and the volume of information available has never been larger. All of this helped to better grasp Earth's information, which in turn encouraged innovation and entrepreneurship. Remote sensing technology has been greatly aided by new approaches and made it possible to see Earth from low-orbit and geostationary satellites simultaneously improved the spatial resolution of remote sensing data (Emery *et al.*, 2017). LULC and land resource management are two examples of remote sensing applications that make considerable use of scene classification, which aims to assign a semantic category to a picture (Zhou *et al.* 2017, Huang *et al.,* 2017). A number of recent LULC classification tasks, such as denoising, cloud shadow masking, segmentation, and classification, have made significant progress (Afrin et al., 2019, Ghaderpour *et al.*, 2020, Zhang *et al.,* 2021). The spectral and spatial features of pixels have been exploited in the development of extensive algorithms. It is, nevertheless, still a difficult task because of the increasing level of abstraction from pixel to object to scene and the intricate geographical distributions of various land cover types. According to Hu *et al.,* it is arduous to train CNNs with smaller datasets, despite CNNs' good capacity to extract high-level and low-level features in previous studies, Yosinski *et al*., 2014 and Yin *et al*., 2017, found that features gleaned from various datasets have consistent behaviour. The final layers of convolution operators gradually transition from general characteristics to features specific to the training dataset. To reach their goals, researchers from all over the world have used advanced algorithms based on soft computing, such as machine learning (Singh et al., 2022 and Kharb *et al*., 2020), response surface methodology (Antil et al., 2021 and 2019), artificial neural networks (Antil *et al*., 2020), and genetic algorithms (Antil *et al*., 2019). Similarly, the development of transfer learning (Bengio *et al*., 2012) has led to the transition of general and specialized CNN layer features. Self-organizing networks trained on Landsat satellite images did better than the maximum likelihood method by getting rid of duplicate data using principal component analysis (PCA). For hyperspectral data categorization, (Chen et al., 2014) used a hybrid framework of DL, logistic regression, and PCA. DL frameworks used stacked autoencoders to extract high-level features. Piramanayagam *et al*., 2016, and Liu *et al.,* 2017 established LULC categorization. With the help of DL, they were able to select better training samples for each iteration (Yu *et al*., 2017). They addressed the lack of tagged data by employing augmentation methods. Yang et al., 2018, increased the generalization capability and performance by merging deep CNN and multi-scale feature fusion with limited data. Liu *et al.* also proposed a deep, random-scale, stretched CNN-based technique for scene classification in 2018. The existence of scenic variety in remote sensing photos hampered categorization performance. As a workaround, SDAResNet (Saliency Dual Attention Residual Network) was used as a workaround, containing both spatial and channel attention, which resulted in superior performance. Xu et al. combined the Recurrent Neural Network and Random Forest for LULC in 2021 to produce an improved classification system.

Every district in Haryana is undergoing through rapid urbanisation which is exerting pressure over the resources. In past years the government has initiated various integrated watershed development programmes in the Shivalik region of the state which had positively impacted the livelihood of people. (Sangwan *et al*., 2006; Singh *et al*., 2007; 2007, and Antil *et al*., 2010; 2010) Hence, it is necessary to observe and analyse the changes in various natural resources with precision in order to mitigate their impact on the resources of the state. A time-series analysis of land use and land cover can predict future changes and avoid overuse and damage to the landscape. (Antil *et al*., 2022).

MATERIALS AND METHODS

Study area

The study was carried out in the district Fatehabad located between $28^{0}48'15''$ to $29^{0}17'10''$ North latitudes and $76^{0}28'40''$ to $77^{0}12'45''$ East with an average elevation of 208 metres from mean sea level having the area of 2520 sq. km which is 5.4% of the state and known as the smallest district of the Haryana state. The climates of the Fatehabad district is tropical desert & steppe, arid and hot mainly dry with very hot summer and cold winter except during monsoon season. The rainfall is unevenly distributed over the entire district. The normal annual rainfall of the district is 373 mm.



Map 1. Location map of study area.

Remote sensing data & Software used

In present study the satellite data of Sentinel-2 Multispectral Imager (MSI) was used. The sensor delivers 13 spectral bands ranging from 10 to 60-meter pixel size downloaded from USGS website. The images for the month of April 2016 and April 2021 were used in all analysis of the study. The window based image analysis software ERDAS Imagine and Google Earth were used for image processing and land use land cover assessment in the study.

Other ancillary data

The base map of the study area was prepared using Survey of India (SOI) Toposheets at 1:50,000 scale and further interpretation of remote sensing data were performed.

Land use and land cover classification

The obtained satellite images of the month of April 2016 and April 2021were analysed for land use land cover changes by adopting level 1classification scheme (Table 1) namely agriculture, water bodies, trees and plantations (forestry), developed land, and fallow land (Fig.1). In this study the supervised classification was conducted using maximum likelihood classifier. This supervised classification with maximum likelihood classifier has been widely used by various researcher (Rao & Narendra, 2006), (Remi et al., 2007), (Chaudhary *et al.,* 2008) for LULC classification in their respective studies. The Methodology adopted for land use and land cover change detection is presented as flow chart manner in Fig. 2.

Pre-processing

This is an essential first step in order to eliminate errors and develop a more accurate relationship between the data and the biophysical properties on the ground. Radiometric, atmospheric, and geometric corrections were made in addition to image gap filling, sub-setting, and enhancement. As part of the pre-processing, the proper band combinations for image categorization have were selected. ERDAS' radiometric correction tool was used

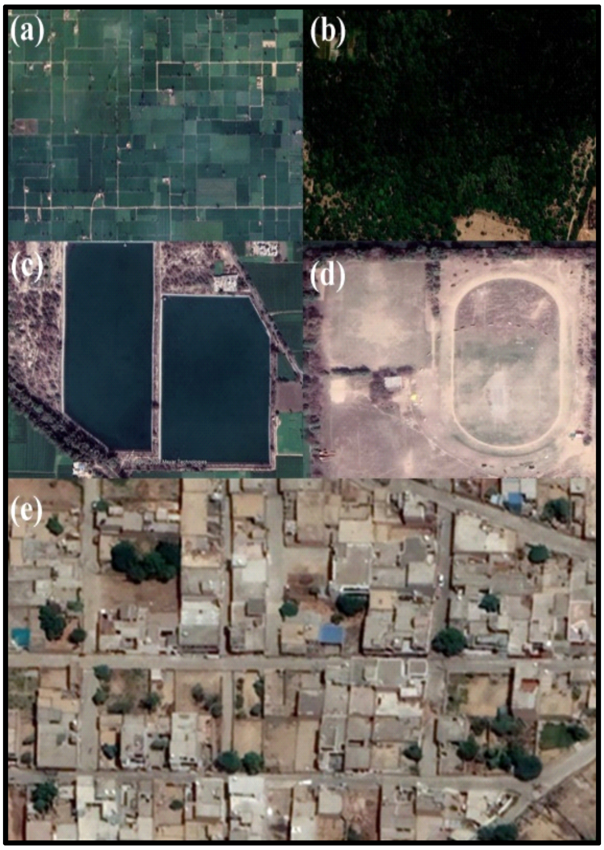


Fig. 1. Satellite images of (a) Agriculture land (b) Vegetation land (c) Water body (d) Fallow land (e) Built up land.

to convert raw data from the sensors (DNs) into top of the atmosphere reflectance (TOA). An empirical method for atmospheric correction was utilised in the current investigation since it is reasonably straightforward and frequently used for categorization and change detection purposes.

Classification

In this investigation, supervised classification method was applied by using ERDAS Imagine, Google Earth Engine and the ground truth data. The signature editor was used to create, manage, evaluate, and amend signatures in the supervised classification process.

TABLE 1

Land use/land cover class and description

S. No.	Class Name	Description
1.	Water body	Canals, rivers, ponds and any reservoir
2.	Build up	Commercial, residential, industrial and transportation infrastructures.
3.	Agriculture land	Cropland and open cultivated area
4.	Vegetation	Trees, plantations and shrub lands
5.	Fallow land	Open land and wasteland area

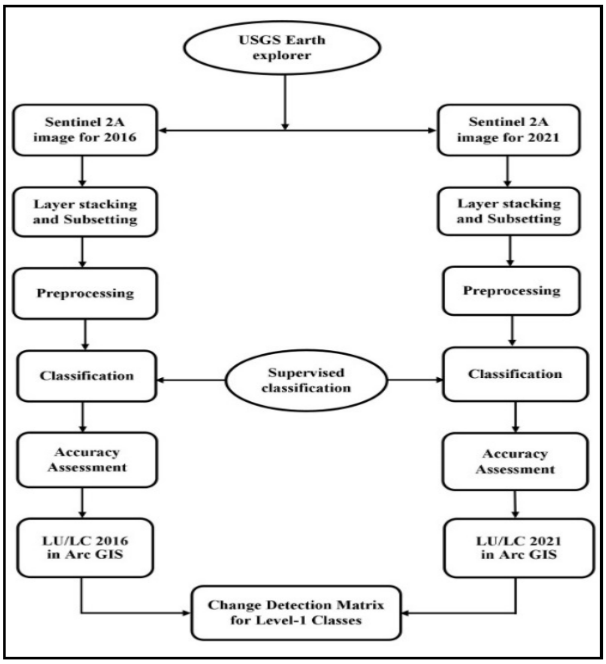


Fig. 2. Methodology for land use and land cover change detection.

Assessment of accuracy

The error matrices and the overall accuracy and kappa coefficient were analysed to evaluate classification accuracy. In addition, for each class, the user's and producer's accuracies, which measure commission and omission mistakes, were acquired. Classification accuracy is considered adequate when it is more than 85% overall. More than 0.85 can be considered excellent or very good agreement for the majority of applications, while values ranging from 0.60 to 0.85 reflect fair or good agreement and values less than 0.60 represent poor agreement.

Change detection analysis

An object or phenomenon's condition can be determined by monitoring it at several points in time, which is known as change detection. A LULC study is of interest because it not only investigates changes that have occurred but also defines the nature of these changes and analyses the spatial extent and pattern of these changes in relation to each other. The following formulae were used to calculate the magnitude of change (MC), percentage of change (PC), and annual rate of change (ARC) for each LULC class over each time period (Alawamy *et al.,* 2020):

$$MC\ (ha) = A_i - A_f$$
$$PC\ (\%) = (A_i - A_f / A_i) * 100$$
$$ARC\ (ha.Year^{-1}) = (A_i - A_f / n)$$
$$ARC\ (\%) = ((A_i - A_f)/(A_i * n)) * 100$$

Where A_i is the class area (ha) at the initial time, A_f is the class area (ha) at the final time, and n is the number of years of the time period (Table 3).

RESULTS AND DISCUSSION

Land use land cover change

During the year 2016, agricultural, vegetation, fallow land and built-up areas were accounted for approximately 195355.90 ha, 21458.32 ha, 13165.08 ha and 10640.60 ha which were 80.72%, 8.8%, 5.54%, and 4.40% of the total area respectively (Fig. 5) while in year 2021, the same agricultural, vegetation, fallow land and built-up areas were accounted for approximately 200899.15 ha, 11968.00 ha, 15325.84 ha and 12880.82 ha which were 82.81%, 4.93%, 6.31%, and 5.30% of the total geographical area, respectively (Table 2).

Change detection analysis

The changes in land cover over the course of five years were noticed in the study. LULC is changing rapidly as a result of urbanization, industrialization and other development activities, which has both positive and negative effects. Each novel phenomenon has repercussions within itself.

In the last five years, the area under water bodies in the study area found in diminishing manner and has decreased by 27%. In 2016, the water body covered a total area of 1,401.90 ha; by 2021, while in year 2017 the area under water bodies was 1,020.42 ha. During the ground truth studies it was noticed that some of the areas are covered by native vegetation or by man-made structures (storage, houses and buildup). In the year 2021, the area under buildup was increased by up to 21% certainly indicating the growth in urbanisation. During this period, the population growth and industrial development may have contributed to urbanization. Simultaneously, a strong association between urban spatial expansion, the geometric centre of a city, and distance from main highways was demonstrated, which showed that roads were the most important factor in urban expansion.

The area under vegetation reduces or declines at a fairly rapid rate. This category comprises forest and plantation land. In 2016, the entire area classified

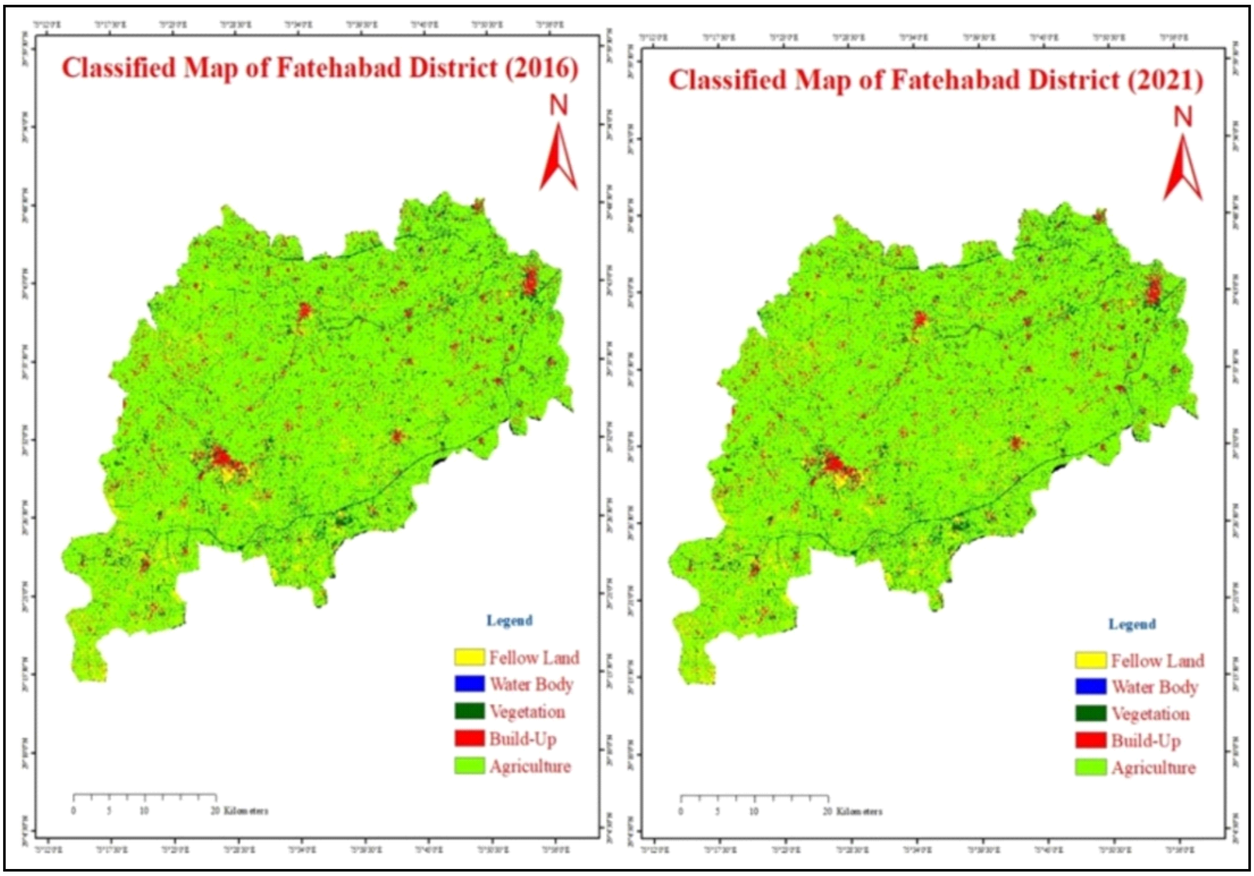


Fig. 3. Classified map of the study area during 2016 and 2021.

as forest was 21458.32 hectares. While It will shrink to 44.2% of the total land area in 2021, averaging 8.4% per year. From 2016 to 2021, approximately 44 % of the area decreased. This is a negative indicator for the environment and wildlife habitats. In five years, the extent of uncultivated land or fallow land increased by 16%. This decrease might be noticed due the selection of imaginary for the month of April as wheat and mustard is major crops in the region and mostly gets harvested in the month of April. In the year 2016, 5.4 % of the total land area is covered by bare soil; by 2021, it has increased upto 6.3 %. On the annual basis, then it increased by 3.2% annually. The coverage area under agriculture sector, however, has notice no notable changes during the past five years (2016-2021). The area under agricultural class has increased by 2 % which is 5,544 hectares. These results are indicative and could be improved further by including more class under classification scheme. Table 4 showed the changes in area of each subsequent class from 2016 to 2021. It presents the change in area within class. It provides information to identify the most exploited class due to human activity or any other reason, which will be further helpful in policy planning for the area. Fig. 6 showed the change detection map for the overall changes in each class.

It was also an area of concern that highest area was transformed from vegetation to agricultural

TABLE 2

Estimated area statistics and %age of the land use cover units in 2016 and 2021

S. No.	Class name	Area (ha) 2016	Area (%) 2016	Area (ha) 2021	Area (%) 2021
1.	Water Body	1401.95	0.57	1020.42	0.42
2.	Build Up	10640.60	4.40	12880.82	5.30
3.	Fallow Land	13165.08	5.43	15325.84	6.31
4.	Vegetation	21458.32	8.86	11968.00	4.93
5.	Agriculture	195355.90	80.71	200899.15	82.81

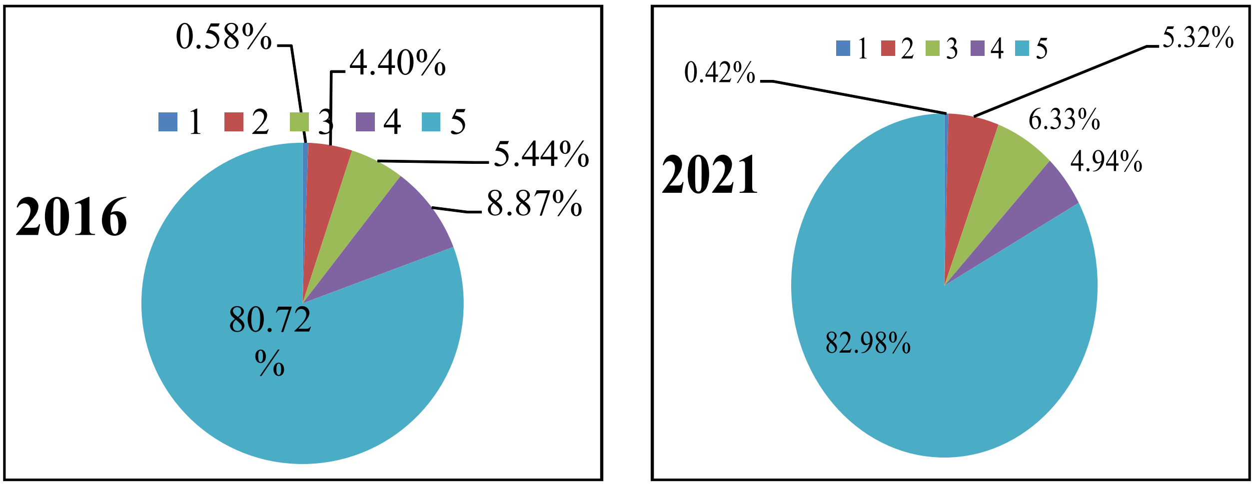


Fig. 4. LULC from the total area in 2016 and 2021(%).

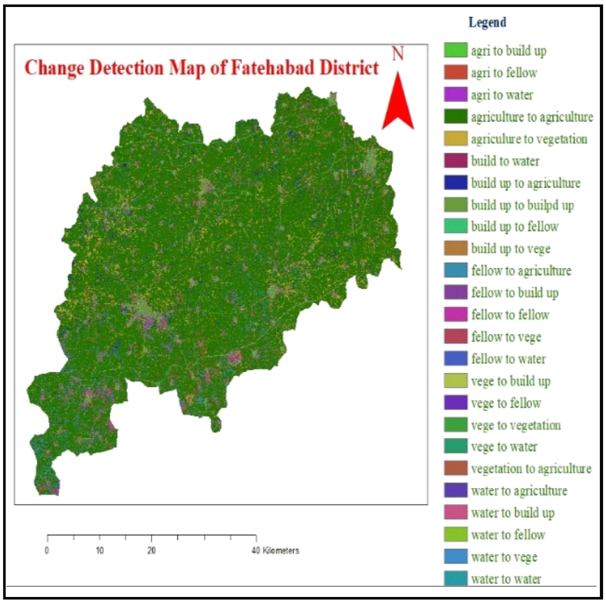


Fig. 5. Change Detection Map for LULC.

land in the study period. According to the statistics provided, the increase in deforestation was mostly due to an increase in agricultural land usage, but some areas natural vegetation have been transformed under man made afforestation in the region. If deforestation continues, soil erosion, high temperatures, and dust storms are inevitable. As a result of these unfavorable consequences, climate change is likely to impact in the future. Change detection map was created in using GIS environment to understand the spatial patterns of change over time after the post-classification comparison of the observed change. In the district due to hot weather the vegetation cover is of prime importance to maintain the microclimate followed by agriculture in terms of importance. There have been significant shifts in land use patterns from agriculture to vegetation and back again due to the widespread adoption of traditional agroforestry practices on previously irrigated agricultural land.

Accuracy assessment

The classification map of 2016 was evaluated using one of the most frequently utilized Kappa accuracy assessment approaches. High quality satellite imagery (10 m in resolution) was used to assess accuracy. The accuracy assessment image year 2016 could not be performed due to lack of availability of clear earth images. Overall kappa values of 0.93 were observed for the classified image of 2021which means the overall accuracy for image classification is excellent.

CONCLUSIONS

This analysis reveals a 27% decline in water bodies, a 44% decrease in vegetation, a 21% increase in builtup and a 16% increase in open land from 2016 to 2021, but no substantial change in area under agriculture has noticed. Here, the decreasing area under vegetation and water bodies are the main concern. Both are essential for maintaining the good microclimate in the district. Consequently, it is a topic of concern and a robust action plan is essential for monitoring and regulating these issues and further some detailed studies including the other co-variables which contributes in change in land use land cover could be performed to obtained more accurate results in the district.

TABLE 3
Summaries of land use land cover changes from 2016-2021

S. No.	Classes	Area (2016) (ha)	Area (2021) (ha)	Change (MC)	% Change in area (PC)	% Change Annually (ARC)
1.	Water Body	1401.95	1020.42	-381.53	-27.21	5.44
2.	Build Up	10640.60	12880.82	2240.22	21.05	4.21
3.	Fallow Land	13165.08	15325.84	2160.76	16.41	3.28
4.	Vegetation	21458.32	11968.00	-9490.32	-44.22	8.84
5.	Agriculture	195355.90	200899.15	5543.25	2.83	0.56

TABLE 4
Changes from 2016 to 2021 in each class

Area change (ha)	Class Names
41.02	Fallow To Water
816.16	Fallow To Vegetation
2106.37	Fallow To Fellow
1472.36	Fallow To Build Up
10350.99	Fallow To Agriculture
486	Water To Water
398.74	Water To Vegetation
45.95	Water To Fellow
129.82	Water To Build Up
412.49	Water To Agriculture
137.96	Vegetation To Water
6826.06	Vegetation To Vegetation
1142.02	Vegetation To Fallow
484.92	Vegetation To Build Up
13627.41	Vegetation To Agriculture
47.54	Build To Water
785.13	Build Up To Vegetation
1026.97	Build Up To Fallow
3516.17	Build Up To Build Up
5497.76	Build Up To Agriculture
181.93	Agriculture To Water
12131.72	Agriculture To Vegetation
3359.84	Agriculture To Fallow
1753.74	Agriculture To Build Up
175280.97	Agriculture To Agriculture

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