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Decadal Land Use Land Cover Change Analysis using Remote Sensing and GIS in Nagpur city of Maharashtra, India

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ABSTRACT

An attempt has been made to analyze the LULC change pattern of Nagpur over the past decade (2010-2020) using remote sensing and GIS. In this study, the LULC map for selected years was prepared by supervised classification using a maximum likelihood algorithm from Landsat data, and accuracy assessment by confusion matrix. The results showed that there were major changes in built-up areas (17.37% expansion) and barren land (19.32% deduction). However, water bodies and forest cover decreased slightly by 0.17% and 0.76%, respectively. Overall, the acreage used for agriculture increased by 2.88% and seems to have been replaced by barren / forest areas. Overall, the LULC change detection algorithms used for classification was very effective with an overall accuracy of 78.88 and 73.30% and a kappa coefficient of 0.74 and 0.67, respectively for 2010 and 2020, considered substantial. Overall, Nagpur's land cover changes constantly due to overcrowding; water and forest bodies are adversely affected by rapid urbanization. The study concludes that previous 10 years of Nagpur LULC trend analysis will help to understand land use change pattern by line departments and take necessary actions to reduce the negative impact of land use and land cover change, as well as proper land use planning and management of the Nagpur city.

Keywords: Land use and land cover; remote sensing and GIS; maximum likelihood; confusion matrix

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INTRODUCTION

Land use change assessments are very important in understanding the relationship between humans and nature (Halimi *et al*., 2017; Pasha *et al*., 2016). Significant changes and technological advances at the regional level have led researchers to collect more information. Over the last three decades, the combination of remote sensing and GIS tools has made it easier to monitor changes in land use land cover (LULC) from the past to the present, as surface changes are more rapid and widespread (Reid *et al*., 2000; Hossain *et al*., 2020). This technology has changed locally and globally and has brought great benefits to the scientific community. Now, LULC is changing rapidly due to rapid urban settlements and overpopulation (López *et al*., 2001; Sikarwar and Chattopadhyay, 2016; Riggio *et al*., 2017). Urbanization is a rapid land use change process that results in a variety of spatial patterns throughout the landscape. Natural resources are also depleted due to corresponding population growth and inadequate land management. However, these changes may be due to several factors also that depend on the socio-economic, political and climatic conditions of each region (Kafi *et al*., 2014). Despite of it, climate change brings a number of challenges, particularly in terms of soil and water quality, quantity, and long-term sustainability, all of which necessitate judicious management (Abhilash *et al*. 2020). In case of land management, optimal land use requires not only information on existing land use / land cover, but also the ability to monitor the dynamics of land use changes. Although, land use management necessitates the creation of a comprehensive land cover (LC) database and expert systems that serve as a foundation for natural resource management and land use planning (Abhilash *et al*. 2021). Therefore, up-to-date information on the speed and nature of change is essential for proper land use planning and management of land resources for productive use. Throughout the history of remote sensing, various change detection algorithms have been used for detection and new technologies are still underway. Data from remote sensing satellites is the primary source of information that provides the potential to obtain information about changes in LULC over the last few decades, using a wide variety of algorithms depending on research needs. Generally, satellite images were used to prepare LULC map using various algorithms like support vector machine, maximum likelihood, artificial neural network etc. Among these algorithms, the support vector machine, maximum likelihood, neural network, and Mahalanobis distance excelled in high accuracy where as Minimum distance, spectral angle mapper, and spectral information divergence achieve moderate accuracy while parallel piped achieves low accuracy (Esmail *et al*. 2016; Zewdie and Csaplovies 2017; Chughtai *et al*. 2021). Keeping in view, an attempt has been made to study land use/land cove changing pattern over decades (2010-2020) in Nagpur city using supervised classification with Maximum Likelihood algorithm. Such type of analysis gives LULC changing pattern that is beneficial for future replanning of natural resources utilization within Nagpur city.

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MATERIALS AND METHODS

Study Area

The study area is Nagpur city located between 21 ° 8 '47.88''N and 79 ° 5'19.89"E, with a total area of approximately 210.72 km² having altitude 310 m in Maharashtra state. (Fig. 1). Summer temperatures in the study area range from 35 ° C to 45 ° C, and winter temperatures from 3.9 ° C to 10 ° C. Average annual rainfall in this area is about 1064mm. Nagpur, the 13th largest city in India has enormous potentiality of natural resources like forest, range, animal resources, water resources, fertile soil and arable cultivable land, fisheries, etc which is attractive to investors.

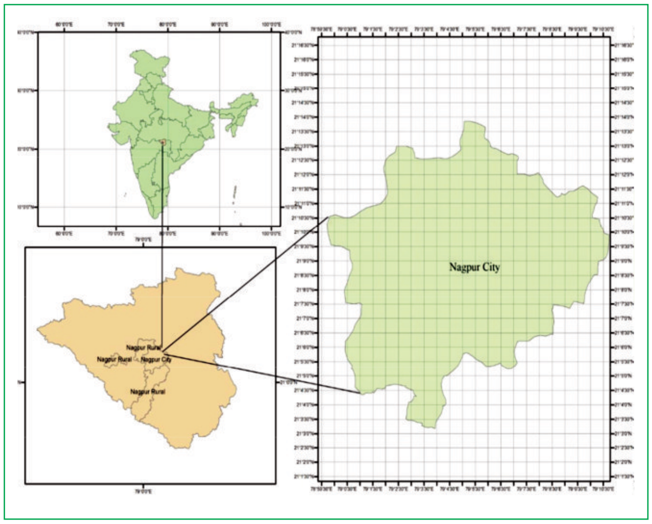

Fig. 1: Location of study area

In this study, Landsat images of 2010 and 2020 were freely downloaded from USGS earth explorer (https://earthexplorer.usgs.gov/). Landsat images are one of the most extensively utilized satellite remote sensing data, and their spectral, geographical, and temporal resolution make them an excellent source of information for mapping and planning applications (Sadidy *et al*., 2009). Then the images were projected in the UTM Zone-44N Coordinate System. False Color Composites were created by stacking bands 5, 4 and 3 (for Landsat 8) and bands 4, 3 and 2 (for Landsat 5) together in the Data Management Tool of Arc GIS. The Image Classification tool bar offers a user-friendly environment for creating training samples and signature files used in supervised classification. In this study, Multiple training samples for five land cover types; Water Bodies, Forest, Agriculture, Built-up and Barren were created and based on training samples, signature file were created. Details used for assigning training samples are presented in Table 1.

Table 1: LULC class description

Sr. No.	Land Cover Class	Description
1	Forest	All forest vegetation types including dense forest, open forest, and scrub or shrub like vegetation features.
2	Agricultural Land	Includes all vegetation features that are not typical of forest, including agricultural and pasture grasslands, recreational grasses.
3	Built-up	Includes all residential, commercial, and industrial development.
4	Barren	Fallow Land Barren or sparsely vegetated areas most often representative of bare earth or soil.
5	Water Bodies	All water bodies including freshwater lakes, rivers, and streams, as well as marine water environments.

Then, using Maximum Likelihood Classification, supervised classification was performed, and areas under each land use type were estimated for both 2010 and 2020.

Accuracy assessment

The accuracy of the LULC classification of the research area has been evaluated using Google Earth utilizing a systematic ground truthing procedure. The confusion matrix or error matrix is the most frequent technique for assessing accuracy based on parameters like ground control points (GCP), classification type, sample size etc (Congalton and Plourde, 2002; Fichera *et al*. 2017; Choudhary *et al*. 2018). In a confusion matrix, the ground truth data was used to generate a collection of random points that were compared to the categorized data. It employed three geoprocessing tools: Create Accuracy Assessment Points, Update Accuracy Assessment Points, and Compute Confusion Matrix, and estimated Kappa coefficient, Overall Accuracy, User Accuracy, Commission and Omission Errors, and displayed the results.

Mathematically, kappa coefficient can be represented as

$$K=\frac{N\sum_{i-1}^{r}(x_d)-\sum_{i-1}^{r}(x_{r+xc+})}{N^2-\sum_{i-1}^{r}{=}_1(x_{r+xc+})}$$

Where, r = number of rows in the classification table; N = total number of points; x_d = sum of correctly classified points along the diagonal; x_{r+} = total number of points in row i; x_{c+}= total number of points in column i

According to the evaluation criteria in Table 2, kappa statistics were also examined.

Table 2: Rating criteria of Kappa statistics

Sr. No.	Kappa statistics	Strength of Agreement
1	<0.00	Poor
2	0.00 - 0.20	Slight
3	0.21 - 0.40	Fair
4	0.41-0.60	Moderate
5	0.61-0.80	Substantial
6	0.81-1.00	Almost perfect

RESULTS AND DISCUSSION

Land use land cover map of Nagpur city for 2010 and 2020 were prepared (Fig. 2) and results showed that in 2010, the area covered under built-up area was about 26.83% (56.54 km^2); 26.27% (55.34 km^2) agriculture; 7.09% (14.94 km^2) Forest, maximum 38.09 % (80.27 km^2) Barren land and only 1.72% (3.62 km^2) covers under water bodies. Similarly, in 2020, area covered under Built-up area, agriculture, forest, barren and water bodies were 44.2 %, 29.15%, 6.33 %, 18.77% and 1.55 %, respectively (Table 3).

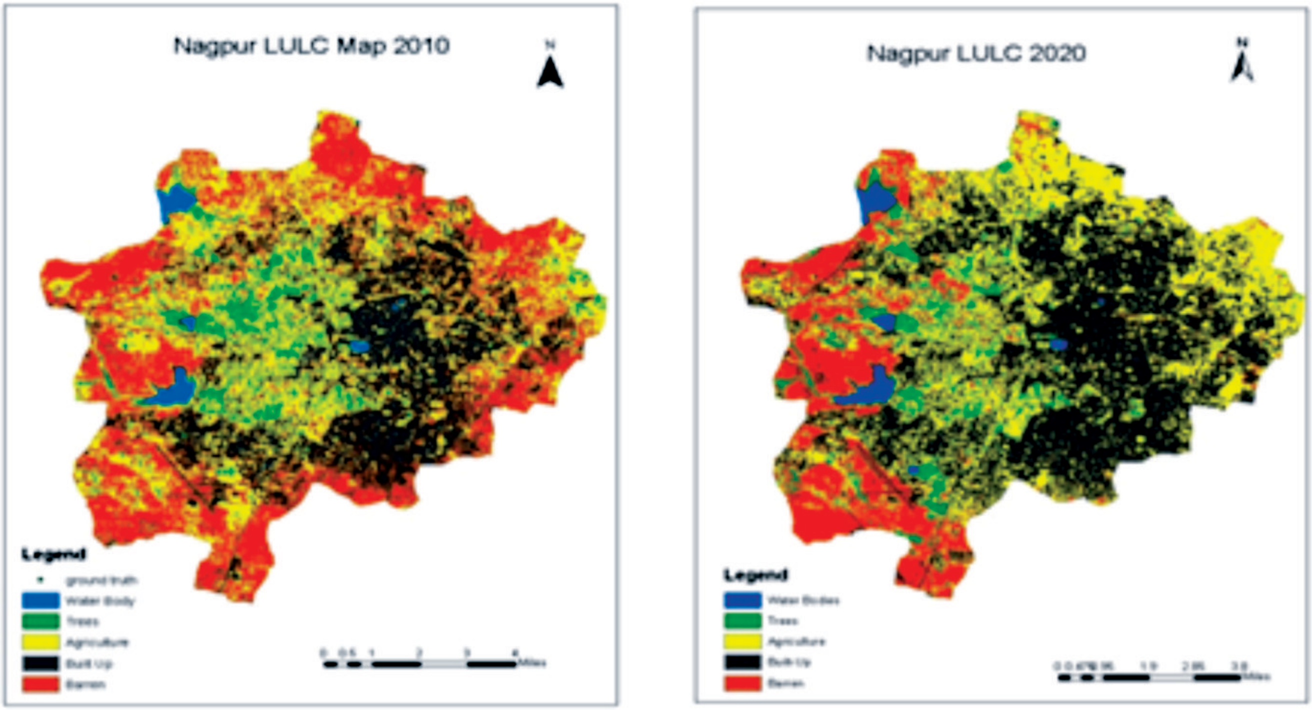

Fig. 2: Land use/land cover map of Nagpur city in 2010 and 2020

Table 3: Area-wise distribution of various land use land cover classes and % change over decade (2010-2020)

Sr. No.	LULC classes	Year 2010 Area (sq.km)	Percent of Total	Year 2020 Area, (sq.km)	Percent of Total	% Change (-ve : decrease +ve increase)
1	Water Bodies	3.6193364	1.72	3.267569	1.55	-0.17
2	Forest	14.9459024	7.09	13.34201	6.33	-0.76
3	Agriculture	55.3450124	26.27	61.422497	29.15	2.88
4	Built-Up	56.5419774	26.83	93.143477	44.20	17.37
5	Barren	80.2663714	38.09	39.560637	18.77	-19.32
	Total Area (sq.km)	**210.72**	**100**	**210.72**	**100**	**0**

Therefore, over decade (2010-2020); it was observed that the area under Water Bodies and Forest has slightly reduced by 0.17 and 0.76 per cent, respectively. Due to deforestation, forest area has been decreased and might be converted into agricultural land or built-up area due to rapid urbanization. As a result, area under Agriculture and Built up in the year 2020 has increased by 2.88 and 17.37 percent as compared to 2010. However, the area, which was barren in 2010 was found to be reduced by 19.32 per cent and seems to be replaced by built-up area (Fig. 3).

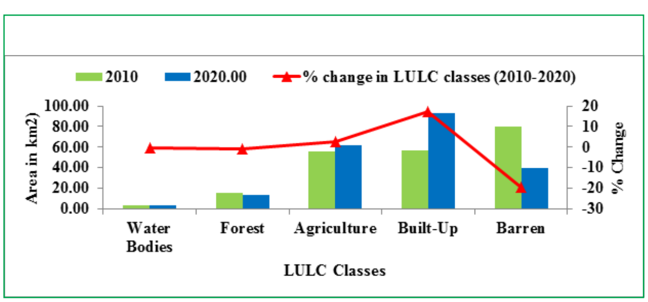

Fig. 3: area covered under different classes of LULC and % change over decades (2010-2020) in study area

Accuracy assessment

For accuracy assessment, Confusion Matrix and accuracy indices for year 2010 & 2020 were prepared and presented in Table 4 and 5, respectively. The results from accuracy assessment showed that, for year 2010 an overall accuracy obtained from the random sampling process for the image is 78.88 %. User's accuracy ranged from 58 % to 82.45 % while producer's accuracy ranged from 58.0 % to 94 %. Forest land use class was found to be more reliable with 82.45 % of user accuracy. In this study an overall Kappa coefficient of 0.74 was obtained which is rated as substantial. Similarly, for year 2020, an overall accuracy obtained from the random sampling process for the image is 73.30 %. User's accuracy ranged from 50.0 % to 97.43 % while producer's accuracy ranged from 52.50 % to 88.0 %. Moreover, the measure of producer's accuracy

Table 4: Confusion Matrix and Accuracy indices for year 2010

Predicted	Land Use	Water	Forest	Agriculture	Barren	Built-up	Total	Commission	Users accuracy
1	Water	43	0	0	0	0	43	0.0	1
2	Forest	0	47	10	0	0	57	0.17	0.8245
3	Agriculture	3	3	29	4	11	50	0.42	0.58
4	Barren	5	0	2	45	5	57	0.21	0.7894
5	Built-up	0	0	9	1	34	44	0.23	0.7727
	Total	51	50	50	50	50	251		
	Omission	0.16	0.06	0.42	0	0.32			
	Producers accuracy	0.84	0.94	0.58	1	0.68			
	Overall accuracy	0.7888							
	Kappa	0.7361							

Table 5: Confusion Matrix and Accuracy indices for year 2020

Predicted	Land Use	Forest	Agriculture	Built-up	Barren	Water	total	Commission	Users accuracy
1	Forest	38	1	0	0	0	39	0.025	0.9743
2	Agriculture	1	31	2	0	0	34	0.088	0.9117
3	Built-up	3	17	40	6	14	80	0.5	0.5
4	Barren	9	0	4	44	5	62	0.145	0.8548
5	Water	0	1	4	0	31	36	1	0
	total	51	50	50	50	50	251		
	Omission	0.16	0.47	0.33	0.12	0.38			
	Producers accuracy	0.8395	0.525	0.6666	0.88	0.62			
	Overall accuracy	0.7330							
	Kappa	0.6664							

(Sensitivity) reflects the accuracy of prediction of the particular category. The User's accuracy reflects the reliability of the classification to the user. Forest land use class was found to be more reliable with 97.50 % of user accuracy. In this study an overall Kappa coefficient of 0.67 was obtained which is also rated as substantial.

CONCLUSIONS

The use of remote sensing and GIS tools has been helpful in discerning the extent of LULC changes that have taken place at Nagpur city over a 10-year period (2010-2020). The study also showed a significant expansion in the size of the Nagpur city. Results showed that over decades (2010-2020); the area under water bodies and forest decreased slightly by 0.17 and 0.76 percent respectively. Due to deforestation, forest area has shrunk and rapid urbanization can convert it to agriculture and built-up areas. As a result, the area used for agriculture and built-up areas increased by 2.88% and 17.37% in 2020 compared to 2010. However, the area under barren land in 2010 decreased by 19.32% and it seems to have been replaced by an inhabited area. Overall, based on the LULC change detection algorithms used for classification, supervised classification was found to be highly effective with an overall accuracy of 78.88 and 73.30% and a kappa coefficient of 0.74 and 0.67, respectively for 2010 and 2020 only, which is considered as substantial. Such type of study definitely helps in land-use planning decisions by policy makers and other government agencies.

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