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Land Use and Land Cover Change Detection and Analysis of Indore District

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Abstract:
Indore, one of the cities in India's central region, is responsible for the sluggish but steady increase of the country's population and industrialisation. Three decades ago, the city's population and size were minimal. In recent years, however, Indore has assumed charge of the city's economic activity in order to assess the changes and determine the city's future planning. To achieve this objective, remotely sensed Landsat 8 pictures from 2014 and 2022 were used to detect changes. This study included both unsupervised and supervised classification methods, however the accuracy of the supervised classification algorithm is approximately 92.5 percent in 2014 and 90 percent in 2022. This outcome informs the formation of the change detection for what has changed.

Keywords: Unsupervised classification, LULC, Indore.

Introduction

LULC is a major technique responsible for construction, planning, climate factors, and managing natural resources such as water and forests, among other things. One of the most important factors is the city's size and population. Gradual population growth is the result of either direct or indirect city expansion. As a city's population grows, the area expands, so agricultural land, fallow land, wetland, barren land, and vegetation land decrease while settlements increase dramatically. (Kafi et al., 2014)

The most effective method for extracting changes in land use and land cover from images taken by space-borne systems is remote sensing and geographic information systems (GIS). The change detection analysis can be done utilising various techniques and certain algorithms. Developed LULC Modelling by integrating data from remote sensing. Future planning will benefit from the advance of LULC from RS and GIS.(Thenkabail et al., 2005)

Indore, the most populous city in the Indian state of Madhya Pradesh, has been designated as a forest ecosystem hotspot. Indore is located in Madhya Pradesh, which has the most forest land in India. With its forests and growing industrial and commercial activities, Indore is the study's focal point. The distribution and condition of forest biodiversity are also impacted by climate change brought on by anthropogenic carbon dioxide emissions. (Gao & Zhang, 2009)

The objective of the study (1) To perform the supervised or unsupervised classification for the Landsat imagery of Indore city of 2014 and 2022. (2) Finding the Accuracy Assessment and kappa statistics of the Indore city of 2014 and 2022. (3) Performing the Change Detection Analysis.

Materials and Methods:

Study Area

Indore is located in the Indian state of Madhya Pradesh, with spatial extension coordinates of 22° 43' 10.48" North and 75° 51' 27.8172" East. With a total land area of 530 square kilometres, Indore is the most densely populated major city in the central province (200 sq. mi). According to the Swachh Survekshan Report 2022, the largest urban sanitation and cleanliness survey in the world and was performed by Mohua for the sixth consecutive year, Indore is the cleanest city in India.

Under Swachh Survekshan 2021, Indore has also been recognised as the nation's first "water plus" city. Only one Indian city, Indore, was chosen for the International Clean Air Catalyst Program. The initiative will be run for five years to purify the city's air with the help of the Indore Municipal Corporation and the Madhya Pradesh Pollution Control Board.

Data Sources:

The data sources used in this study are shown (Table 1).

Table 1. Data Sources used in the research.

Data	Time series	Spatial Resolution	Source
Landsat - 8	2014	30m	https://earthexplorer.usgs.gov
Landsat - 8	2022	30m	https://earthexplorer.usgs.gov

Methods

2.3.1 LULC Classification

The various LULC Classes are categorised using a Level 1 classification method to simplify change detection analysis. Waterbodies, vegetation, built-up areas, barren land, and agriculture are all included in this LULC classification. Waterbodies like lakes, streams, build-up areas like settlements, roads, and Industries, Barren land like waste land, dumping grounds, Vegetation like an evergreen forest, deciduous forests, scrubs and Agriculture like fallow land, etc. According to the NRSC Scheme, level 2 and level 3 are included in these five classes.

Figure 1. Flow Chart of the Research Methodology

Image Classification

Unsupervised Classification:

The categorisation of the classes into groupings or clusters unsupervised using multidate imageries. Isodata and K-mean are the algorithms used to identify the LULC Changes. But because some LULC Classes are misclassified, it didn't produce the exact results we hoped for. The maximum likely wood algorithm is used for the supervised classification, and we can use false colour composition to determine the ground features of the area of interest (AOI). The map is produced by designating an area in the map based on the colour assigned to that category and the spectral homogeneity of the pixels in the chosen size. The spectral signature is taken for each class using Erdas Imagine. After the classification process, the accuracy was Good (92% and 90.0%), and the kappa statistics were 0.85 and 0.81 for 2014 and 2022, respectively.(Tavares et al., 2019)

Post Classification

Two independent images are used for the post-classification procedure to create the change detection matrix after the classification. Change classes can be obtained using a "from- To" categorisation table. This identification method is efficient because it will analyse how much area has been taken over the last eight years.

Accuracy Assessment

To confirm how accurately the categorisation matches the ground, the overall accuracy of post-classification images is performed. High-resolution images, such as (Sentinel, Google Earth Pro and Base Map) The table of accuracy provides the four different categories of accuracy: (1) Overall Accuracy; (2) Producer Accuracy, (3) Users Accuracy, and (4) Kappa Statistics. (Derdouri et al., 2021)

I. Overall Accuracy

Overall, the accuracy tells us what percentage of the reference sites were accurately mapped. In most cases, the overall accuracy is given as a percentage, with 100% accuracy denoting a perfect classification in which all reference sites were correctly categorised. Although it is the simplest to compute and comprehend, overall accuracy only offers the map user and producer basic accuracy data.

The areas that were accurately classified are represented by the diagonal elements. You divide the entire number of correctly classified sites by the total number of reference sites to determine the overall accuracy.

II. **Producers Accuracy**

This is the probability that a particular land cover of an area on the ground is classified as such or the frequency with which actual features on the ground are accurately depicted on the classified map. Producer's Accuracy Omission Error, where Omission Error is the complement of Producer's Accuracy. Additionally, it is calculated as the total number of reference sites for that class divided by the number of accurately classified reference sites.

III. **Users Accuracy**

The user's accuracy tells us how frequently the class depicted on the map will be present in reality. This is what reliability means. User Accuracy Commission Error, where User Accuracy is the complement of Commission Error. The User's Accuracy is calculated by dividing the total correct categories for a given class by the number of rows.

IV. **Kappa Coefficient**

A discrete multivariate technique used in accuracy evaluation is kappa analysis. In essence, Kappa measures how well the classification worked in comparison to simply assigning values at random. The Kappa coefficient expresses the proportionate reduction in error generated by a classification process compared with a completely random classification error.

Results and Discussion:

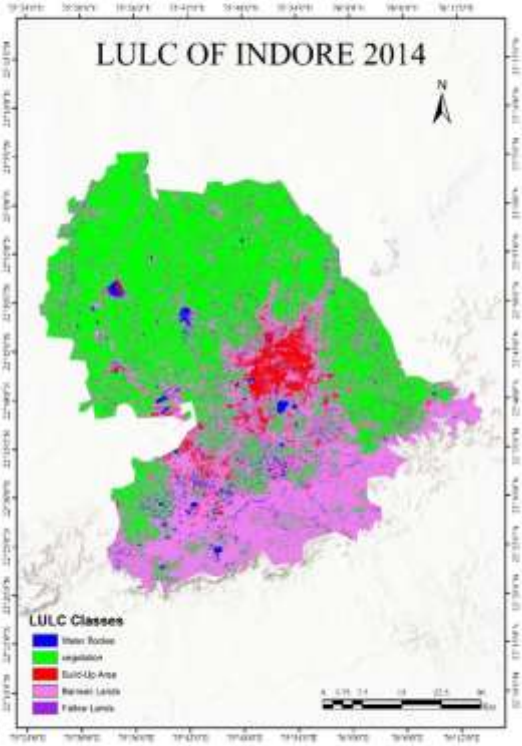

Figure 2. LULC Map of Indore in 2014

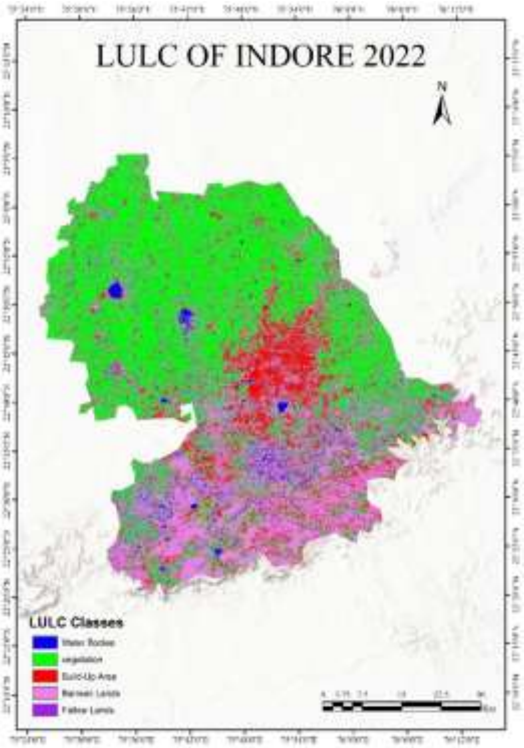

Figure 1. LULC Map of Indore in 2022

The LULC Classification followed the five categories of LULC data from the chosen AOI that will be used in the change detection process. The accuracy assessment resulted in a kappa coefficient of 0.85 and a total accuracy for 2014 of 92.0%. Users' accuracy results are likewise above 90%, and producers' class accuracy is above 90%.

Table 2: Confusion Matrix of 2014

Table 2.Confusion Matrix of Classified Image (2014)

Classes	Waterbodies	Vegetation	Build-up	Barren land	Agriculture	Producers Accuracy	Users' accuracy
Waterbodies	1	0	0	0	0	100%	100%
Vegetation	0	5	0	0	0	90.0%	96.03%
Build-up	0	23	1	1	0	90.32%	90.32%
Barren land	0	0	1	1	15	92.01%	95.03%
Agriculture	0	3	0	0	0	95.00%	91.5%

Kappa Statistics = 0.8505 Overall Accuracy = 92.00%

The LULC Classification followed the five categories of LULC data from the chosen AOI that will be used in the change detection process. The accuracy assessment resulted in a kappa coefficient of 0.81 and a total accuracy for 2022 of 90.0%. Users' accuracy results are likewise above 85%, and producers' class accuracy is above 85%.

Table 3. Confusion Matrix of Classified Image (2022)

Classes	Waterbodies	Vegetation	Build-up	Barren land	Agriculture	Producers Accuracy	Users' accuracy
Waterbodies	1	0	0	0	0	100%	100%
Vegetation	0	26	1	1	0	93.55%	93.55%
Build-up	0	0	4	1	0	80.00%	80.00%
Barren land	0	1	2	12	1	84.00%	85.80%
Agriculture	0	0	0	0	1	100%	100%
Kappa Statistics = 0.8103				Overall Accuracy = 90.00%			

Table 4. "From - To" changes in the LU/LC classes from 2014 to 2022.

SN	Changes in LULC Class	Area Changes (Km2)	SN	Changes in LULC Class	Area Changes (Km2)
1	Water_Bodies - Waterbodies	39.64	14	Buildup_area - Barren_Land	44.24
2	Water_Bodies - Vegetation	6.89	15	Buildup_area - Agriculture	2.13
3	Water_Bodies - Buildup_area	4.95	16	Barren_land - Waterbodies	25.24
4	Water_Bodies - Barren_Land	31.73	17	Barren_land - Vegetation	349.9
5	Water_Bodies - Agriculture	2.92	18	Barren_land - Buildup_area	260.72
6	Vegetation - Waterbodies	11.39	19	Barren_land - Barren_Land	81.27
7	Vegetation - Vegetation	1412.05	20	Barren_land - Barren_Land	56.27
8	Vegetation - Buildup_area	27.88	21	Barren_land - Agriculture	66.73
9	Vegetation - Barren_Land	339.51	22	Agriculture - Waterbodies	1.01
10	Vegetation - Agriculture	127.88	23	Agriculture - Vegetation	68.07
11	Buildup_area - Waterbodies	4.3	24	Agriculture - Buildup_area	8.47
12	Buildup_area - Vegetation	22.86	25	Agriculture - Barren_Land	50.85
13	Buildup_area - Buildup_area	121.37	26	Agriculture - Agriculture	12.29

Discussion:

In 2014, there were 86.12 sq km of waterbodies, 1919.02 sq km of vegetation, 194.91 sq. km of built-up area, 1563.43 sq km of barren land, and 140.729 sq km of agricultural land. As a result, this class has changed "from - to" over the previous eight years. The table below displays Indore's change detection between 2014 and 2022. The conversion of waterbodies to agriculture, vegetation to agriculture, build-up into barren land, barren land into build-up, and agricultural land into build-up all occur in 2022, with parts of the five classifications remaining the same from 2014 to 2022.

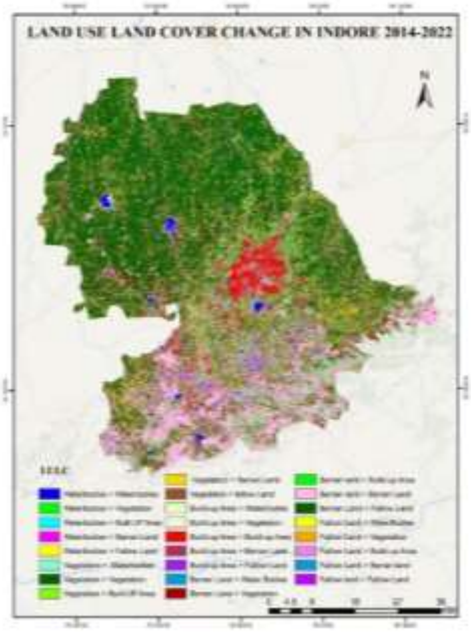

Figure4. Land Use and Land Cover change map of Indore during 2014 to 2022.

3.1.1 Waterbodies

The water bodies, including rivers, waterlogged areas, wet fields, and small ponds, decreased from 86.126 to 39.642 square kilometres in 2022 due to gradual increases in the city's urbanisation population. As a result, more people are settling near lakes, ponds, and rivers.

3.1.2 Vegetation

Over the past ten years, there has been a decline in the shrub/grass, which is made up of trees, shrubs, and grasses. Deforestation has occurred due to certain business operations. Even though people are involved in other activities in urban areas, there has been a recorded decrease in 1919.025 sq km in 2014 and 1412.053 sq km in 2022.

3.1.3 Build-up area

According to the analysis, the built-up area, which includes high densities, a road network, and other man-made structures, has seen a large expansion. The built-up area's overall size, which was expected to be 194.26 square kilometres in 2014, will grow to 212 square kilometres by 2022. Due to the growth of industries, urbanisation, and employment opportunities, people are moving from rural to urban areas.

3.1.4 Barren land

The city's barren land is separated into dumping waste and land that is not used for human activities. Still, throughout this study's eight years, the amount of empty land has reduced due to the city's rapid expansion in size and people. Indore's arid land area was recorded as 1564.434 sq km in 2014 and 81.27 sq km in 2022.

3.1.5 Agriculture

This makes up the agricultural land primarily utilised to grow cereals like maise, microgreens, potatoes, radishes, and tomatoes. The analysis revealed a sharp decline in agricultural land accessible within the Indore. In 2014, there were 140.729 square kilometres of agricultural land, and in 2022, there were around 12.294 square kilometres.

4. Conclusion

Remote sensing and GIS methods were useful in identifying the LULC change in Indore during the past eight years. The survey also showed that the size of Indore has significantly increased. Due to the city's rapid growth, all LULC classes have decreased except those in the construction zone. Due to its business activity, Indore is also known as the "mini-Mumbai" and is growing economically and in its educational sectors. People from Madhya Pradesh's rural districts are moving to Indore because of the city's economy and a six-year streak of cleanliness as India's cleanest city.

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