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LAND USE LAND COVER DISTRIBUTION AND CHANGE DETECTION IN CHENNAI USING GEOSPATIAL TECHNOLOGY

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Abstract

Cities are a draw for expanding the nation's social, economic, and political context. It can build large-scale and small-scale businesses, academic facilities, government agencies, and other entities. As a result, more people migrate to urban areas from rural areas or move from one urban centre to another. Consequently, the population density is increasing in several areas of the cities. There would be a significant alteration and adjustment in the way the land is used as a result. Therefore, a thorough analysis and several assessments are needed for such a development to maintain the urban environment and prepare for potential future calamities. Accordingly, the study's primary goal is to determine the change in land use and detect land cover in Chennai. Using Land sat 4-5, and 8, 30 m resolution images, remote sensing data, satellite imagery, and image processing techniques were used to determine land cover changes between 1997 and 2017. The modifications were located using the ERDAS and Arc GIS software. Five categories of land cover—water body, vegetation, agricultural, barren terrain, and built-up area—were used in the categorization. The images' pre-processing and classification had undergone comprehensive analysis, and the accuracy assessment had been tested separately using the kappa coefficient. The change detection indicated that the shifting of barren land (54.91 sq. km), agriculture (9.10 sq. km), and vegetation (9.03 sq. km) had significantly changed the built-up area. The accuracy assessment showed that the overall accuracy is 96.88 % and 94.59 %, with a kappa coefficient of 0.95 and 0.87.

Keywords: Land Use Land Cover, Supervised Classification, Kappa coefficient, Change Detection, Accuracy Assessment.

1. Introduction

Land use/land cover (LULC) changes are critical in studying regional, local, and global climatic change. Land cover relates to how much of the Earth's surface is surrounded by forest lands, wetlands, impervious surfaces, agricultural areas, and other land and water. Land use refers to how humanity uses the terrain for growth, conservation, or a combination of the two. Recreational spaces, wildlife habitats, farmland, and built-up land are all examples of land use.

The nature of a country's land use and land cover results from how humans have used environmental and sociological variables over time and place. Because of intense agricultural and population demand, the land is becoming a precious resource. To choose, plan, and execute land use schemes that will satisfy the growing demand for fundamental human requirements and welfare, knowledge of land use/land cover and options for their best use is crucial. This data also aids in tracking the trends in land usage due to shifting needs brought on by population growth. The Remote Sensing Satellites used for this study are Landsat, IKONOS, CARTOSAT, RADARSAT, etc.

In GIS, change detection refers to a technique for determining how a particular region has changed across two or more eras. This is beneficial for changing land use, deforestation rates, shoreline changes, urban sprawl, etc. Analyzing differences among aerial images of the same specific region obtained at various times allows for the discovery of changes. Some of the various change detection approaches include the use of image differencing, ratioing, image regression, PCA transformations, pixel based, OBIA, manual classification, chi-square, post-classification comparisons, etc.

As a result, this research aims to map out the condition of land use and land cover in Chennai between 1997 and 2017 to identify the land consumption levels and the alterations that have occurred in this condition, especially in built-up land, to forecast potential risks that may occur in this prestige in the next

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10 years using both GIS Analysis and Remote Sensing Data. This study aims to produce a Land use land cover map of Chennai between 1997 and 2017 and to detect changes in the Built-up area.

2. Study Area

Chennai, previously Madras, is the capital of Tamil Nadu state in southern India and is situated on the Bay of Bengal's Coromandel Coast. Chennai, sometimes known as the "Gateway to South India," is an important administrative and historic site. Chennai is the fifth-most populous metropolis in India and is situated at latitude 1304'2.7804" N and longitude 80 014'15.4212" E in the country's southern region. On the other side, they converge in saltwater areas where mangroves have been planted around Ennore. This mangrove environment brings a wide variety of living forms. When it comes to alterations in human population, land usage, and land cover, the Chennai District is extremely valuable. The second-largest beach in the universe is there. The canal flows north to south, and the stream flows east, defining the boundaries of the realm. Significant soil types include well-drained sandy and clayey soils adjacent to Public Lake on the Northern Coast.

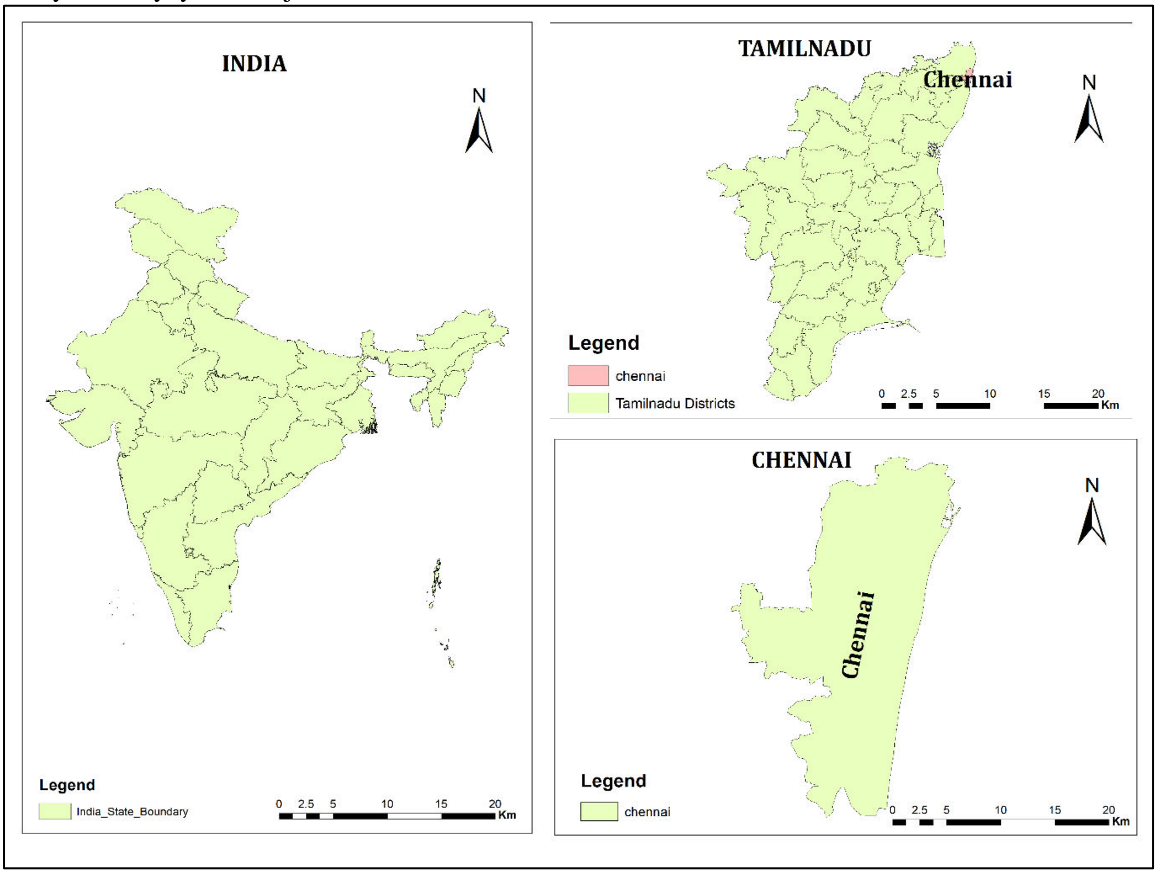

Figure 1 Study area Map of Chennai

3. Materials and Methodology

Landsat 4-5 TM pictures and Landsat 8 OLI/TIRS data were obtained for this investigation between 1997 and 2017. Using ArcGIS Software, the administrative border of Chennai is retrieved as a shapefile. The dataset collected for the investigation is shown in the table. Landsat satellite images were collected from the United States Geological Survey (USGS), an open resource that offers topographical and geographical pictures of the necessary area. The following remote sensing methods include image pre-processing, processing, analysis, and evaluation via software such as ERDAS IMAGINE 2015 Version, ArcGIS 10.7 Version, and so on.

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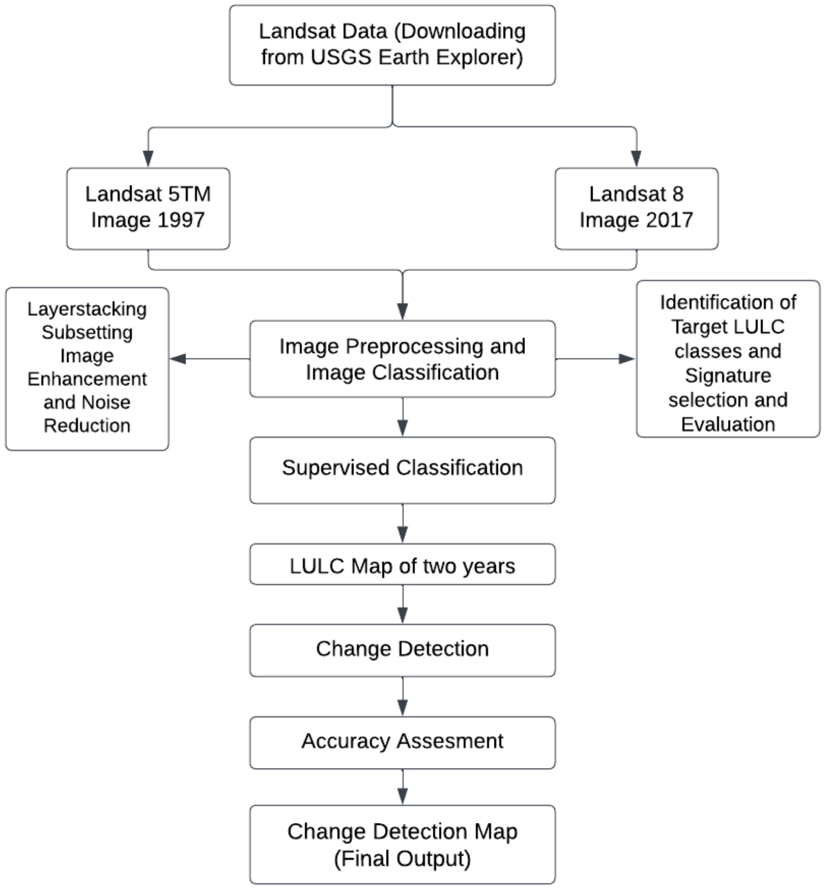

Figure 2 Methodology Chart

Leveraging satellite data, other themed layers were also created in a GIS context. Eventually, all the content is linked to GIS software to produce various graphs and maps for interpretation. Those data sets were employed in categorizing land cover and land use. During the research, cloud-free satellite photos were selected in a certain month of these two years to decrease image differences due to regular intervals or yearly variations(1).

Table 1 Data, sources, Spatial Resolution and Year

Data	Source	Spatial Resolution	Year
Landsat 5 (MSS, TM)	USGS Earth Explorer	30 m	1997
Landsat 8 (OLI, TIRS)	USGS Earth Explorer	30 m	2017

3.1. Land use and land cover classification

The actual data must be appropriately pre-processed and prepared before image classification can be performed to correct for errors caused by atmospheric, radiometric, and earth geometry factors. Radiometric calibration, geometric rectification or picture registration, atmospheric correction, and topography correction have all been standard pre-processing steps.

3.2. Supervised Classification

In this procedure, pixels that depict characteristics we are familiar with or could recognize with the use of data from different sources (such as Google Earth) are chosen. Before choosing training samples, we needed to be familiar with the data, the target classes, and the methods to be applied(2). We controlled the categorization of pixels as they were allocated to a class value by assigning priority to various classes.

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3.3. Accuracy Assessment

To evaluate a categorized image's efficiency and estimate its correctness, it must be contrasted to reference points presumed to be accurate. By contrasting the classified map with a base map, the method was used to determine the precision of picture classification. Consequently, the reports on overall accuracy, user accuracy, and producer accuracy examined using the Kappa coefficient must be included in the complete accuracy evaluation.

3.4.Change Detection

Identifying which land-use class is shifting to the other is the purpose of change detection. The techniques for detecting land changes that are most frequently employed include image overlay, classifications comparisons of land cover statistics, change vector analysis, principal component analysis, image rationing, and the differentiation of normalized difference vegetation index(3). Measurements of the land cover were compared using classifications in this study. Each year, the areas covered by each land cover were compared. Finally, every land use/cover class's modification had its directions assessed.

4. Results and Discussion

4.1. Land use and land cover analysis

A confusion matrix was utilized to evaluate classification accuracy, taking into account overall accuracy, user accuracy, and producer accuracy. The accuracy of the classification must first be evaluated using the established Kappa statistics(2,4).

4.1.1. Overall Accuracy

This accuracy provides the confusion matrix's overall findings. It is determined by dividing the number of accurate pixels (diagonal values) by the total number of pixels in the confusion matrix(2). A valid land cover categorization requires an accuracy value of at least 85%. On the other hand, accuracy levels that certain users consider appropriate for a particular task may not be found satisfactory by other users.

4.1.2. Kappa Coefficient (KC)

The Kappa statistic was once employed to assess the degree of agreement among two sets of dataset categorizations. And used to assess the prediction model's accuracy by gauging how well it agrees with a group of sample points collected through field research(2).

Generally, the results showed that the overall accuracies were 96.88% and 94.59% for the years 1997 and 2017, respectively. This result has fulfilled the minimum accuracy for land cover change. The kappa coefficient of the classification was in 1997 and 2017, respectively. Thus, the classification scale is perfect and excellent in 2017 and 1997, respectively.

4.2.Land use and land cover maps

The spatial analysis had carried out to describe land cover change patterns and overall land-use changes with time. Waterbody, Built-up areas, forests, agriculture, and barren lands were the primary land use and land cover classes of the Study area. Land use land cover change and detection showed a change of most vegetation to Built-up area(1). This result showed that nowadays, the vegetation was changed into built-up areas.

Images are classified into four land use classes vegetation, water body, barren land, agriculture, and built-up. Land cover maps were derived using a supervised classification based on Landsat images for 1990 and 2020. Then, land cover maps were analyzed to understand the changes in land use and land cover patterns. Barren land was the main land cover in 1997, with 76.48 sq. km of the total area of the Chennai district, followed by Built-up area (52.24 sq. km), vegetation (24.97 sq. km), agriculture (21.29 sq. km) and water body (19.77 sq. km). The area of vegetation decreased from 1990 to 9.05 (sq. km) in 2017. On the other hand, the Built-up area increased to 125.34 sq. km in 2017. The accuracy assessment showed that the overall accuracy is 96.88 % and 94.59 %, with a kappa coefficient of 0.95 and 0.87.

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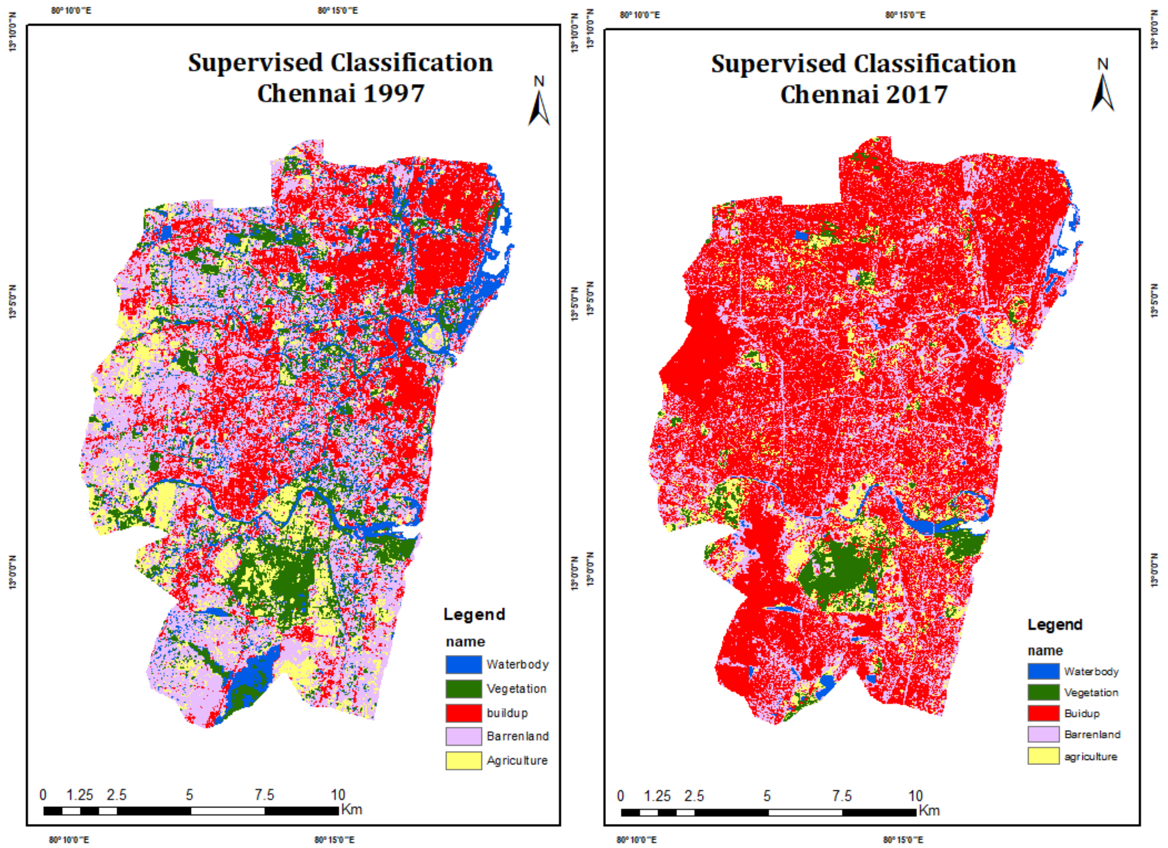

Figure 3 Supervised Classification 1997 & 2017

Table 2 LULC Classes and Area (in sq. km)

LULC	***1997 – Area(sq.Km)***	***2017 - Area(sq.Km)***
Waterbody	19.77	3.042
Vegetation	24.97	9.055
Built-Up	52.24	125.34
Agriculture	21.29	14.79
Barren Land	76.48	42.56

Table 3 Accuracy Assessment Table

LULC Classes	Waterbody	Vegetation	Built-Up	Agriculture	Barren Land	Total (User)
	5	0	0	0	0	5
Waterbody	0	6	0	0	0	6
Built-Up Area	0	1	8	0	0	9
Agriculture	0	0	1	9	0	10
Barren Land	0	0	0	0	7	7
Total	**5**	**7**	**9**	**9**	**7**	**37**

$$\text{Overall accuracy} = \frac{\text{Total Number of Correctly Classified Pixel (diagnol)}}{\text{Total number of referenced pixels}} \times 100$$

$$\frac{35}{37} \times 100 = 94.59$$

Table 4 LULC Classes, User's and Producer's accuracy

LULC	**Users Accuracy**	**Producers Accuracy**
Waterbody	100%	100%
Vegetation	85%	100%
Built Up	88%	88%

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Agriculture	100%	90%
Barren Land	100%	100%

User Accuracy = $\frac{\text{Number of correctly classified pixels in each category}}{\textit{Total No.of classified pixels in that category (The Row Total)}}$ x 100

Producer Accuracy = $\frac{\textit{Number of correctly classified pixels in each category}}{\textit{Total No.of classified pixels in that category (The Column Total)}}$ x 100

Overall Accuracy = $\frac{\textit{Total No.of corectly classified pixels (Diagonal)}}{\textit{Total No.of Refernce Pixels}}$ x 100

Kappa Coefficient (T) = $\frac{(TS*TCS) - \varepsilon\,(Column\,Total*Row\,Total)}{TS\,2 - \varepsilon\,(Column\,Total*Row\,Total)}$ x 100

$$\frac{(37*(5+6+8+9+7)-(5*5)+(7*6)+(9*9)+(9*10)+(7*7)}{37^2-287} = \frac{1295-287}{1157} = 0.87\% = 87\%$$

4.3. Change Detection Analysis

Remote sensing image-based methods for detecting changes in land use and land cover have been extensively used in LULC change analysis, sustainable use of natural resources, and environmental control and preservation(5). Each land cover class's percentage area was calculated using Arc GIS from supervised classified images for each year. The change detection indicated that the shifting of barren land (54.91 sq. km), agriculture (9.10 sq. km), and vegetation (9.03 sq. km) had significantly changed the built-up area. Moreover, the area of agriculture (4.89 sq. km) and vegetation (4.71 sq. km) had changed slightly into barren land. This finding was similar to the land use land cover of Chennai reported that there was significant urban growth happened during the past decades.

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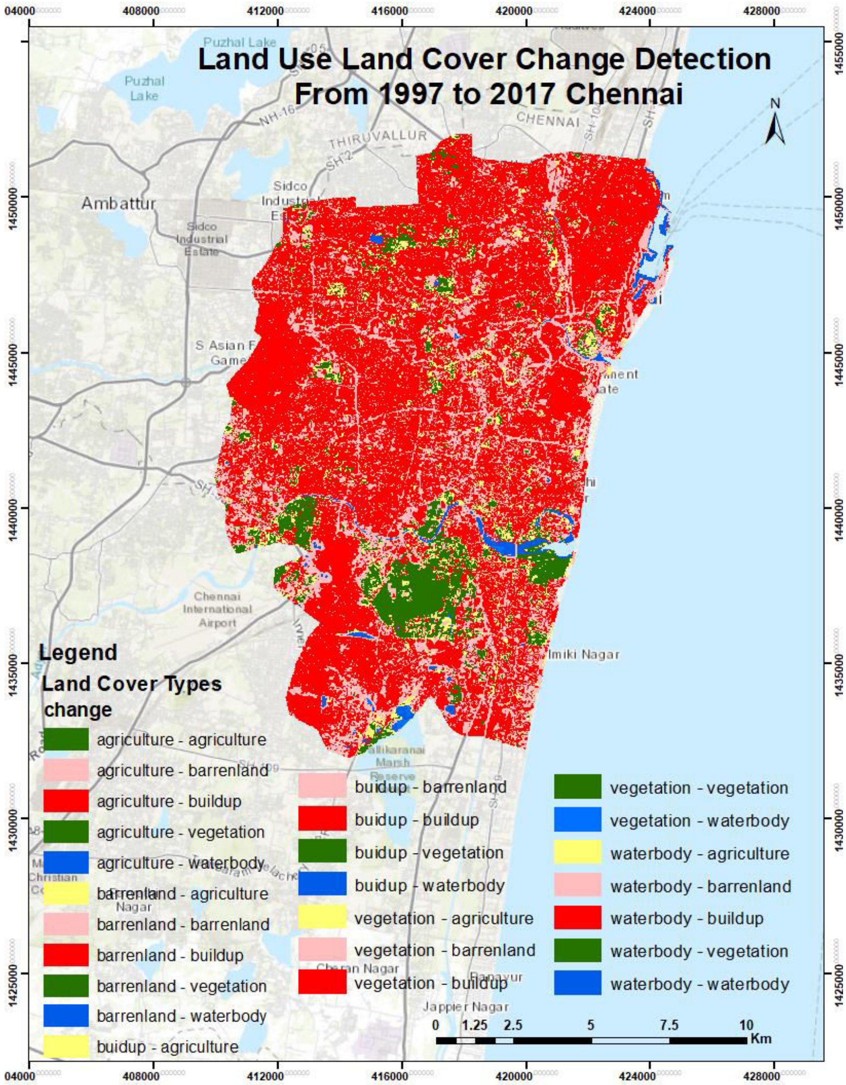

Figure 4 Change Detection

Table 5 Changes in classes and Areas (sq. km)

Change (1997 - 2017)	Change in the area (sq. km)
Agriculture - agriculture	5.26
Agriculture - barren land	4.89
Agriculture - Built-up	9.10
Agriculture - vegetation	1.88
Agriculture - waterbody	0.13
Barren land - agriculture	3.40
Barrenland - barrenland	17.46
Barrenland - Built-up	54.91
Barrenland - vegetation	0.38
Barrenland - waterbody	0.27
Built-up - agriculture	0.33
Built-up - barren land	8.45
Built-up - Built-up	43.34
Built-up - vegetation	0.04
Built-up - waterbody	0.08
Vegetation - agriculture	4.67
Vegetation - barrenland	4.71
Vegetation - Built-up	9.03

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Vegetation - vegetation	6.24
Vegetation - waterbody	0.31
Waterbody - agriculture	1.12
Waterbody - barrenland	7.00
Waterbody - Built-up	8.88
Waterbody - vegetation	0.51
Waterbody - waterbody	2.23

5. Conclusion

According to remote sensing and GIS research, the Chennai region is seeing rapid changes in land use and land cover due to urbanization and industrial growth. The quantitative evaluation of land use/land cover changes generated from multi-date remote sensing data indicates that there has been a concurrent drop in farmland and vegetation and an increase in settlement areas. Significantly diminished inland freshwater resources, primarily due to development and lake/pond denudation. The findings of this study's remote sensing and GIS analyses demonstrate the strong correlations between changes in the vegetative space and the sustainability practices of the Chennai metropolis. According to specialized forestry and intensive eucalyptus plants in this region, the reserve forest area has increased during the past 15 years. The results of this study will also be beneficial in determining the best ways to increase the vegetation cover in Chennai. However, by altering the variables and data covers, this model might be used in various cities. It will make it easier to comprehend the spatial impacts of a shift in the amount of vegetation on the natural aspects of a particular city.

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