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Assessment of spatial and temporal change in the Yellapur forest division, Uttara Kannada district, Karnataka, using a remote sensing approach

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Abstract
The study assessment of spatial and temporal change in the yellapur forest division, Uttara Kannada district geographically positioned between 74° 25' to 75° 6' East longitudes and 14° 44' to 15° 7' North latitudes. Spatial and temporal change detection is the process of identifying and quantifying the spatial changes of any natural or manmade phenomenon from satellite images of different periods. The LULC map for 2000, 2010 and 2023 was generated using Google Earth Engine. The spatial and temporal changes from 2000 to 2023 in the Yellapur forest division were assessed using QGIS.
Vegetation, which covered 178,108 ha (90.35%) in 2000, decreased to 160,018 ha (81.68%) by 2023, an 8.67 per cent reduction due to deforestation, agricultural expansion and infrastructure development. Agricultural land increased from 12,369 hectares (6.27%) in 2000 to 16,976 ha (8.61%) in 2023, driven by population growth and rising food demand. The built-up area expanded significantly from 4,564 hectares (2.32%) in 2000 to 17,413 hectares (8.83%) in 2023 mainly due to urbanization and infrastructure growth.
Significant land use changes were observed, with notable transitions from vegetation and agricultural land to built-up areas due to urban expansion and infrastructure development. Approximately 15,784.92 hectares of vegetation and 4,904.19 hectares of agricultural land were converted to built-up areas, while 5,263.92 hectares of vegetation were turned into farmland. Around 2,420.82 hectares of agricultural land reverted to vegetation, highlighting dynamic shifts driven by human activities such as plantations In 2000, the overall accuracy was 96.07 per cent with a Kappa coefficient of 0.92. By 2010, accuracy was 95.29 per cent (Kappa 0.91) and in 2023, it reached 95.45 per cent with a Kappa coefficient of 0.94, indicating strong agreement throughout the years.

Keywords: Land use land cover, kappa coefficient, spatial and temporal change

Introduction
Forests are essential ecosystems that play a key role in maintaining ecological balance. They provide habitats for a wide variety of plant and animal species, help regulate the climate by absorbing carbon and contribute to the water cycle through transpiration. Forests are classified into types like tropical, temperate and boreal, depending on their location and climate. In addition to offering resources such as timber, fuel and medicinal plants, they also support the livelihoods of many communities. However, deforestation and degradation continue to threaten biodiversity and reduce carbon storage.
Remote sensing, as a discipline, plays a pivotal role in our understanding of the Earth's complex systems and processes. It encompasses the science and technology of acquiring information about objects, areas, or phenomena without direct physical contact (Lillesand *et al.*, 2015) [13]. In the context of forestry, remote sensing techniques are indispensable for gathering data on biophysical parameters crucial for effective forest management. By combining information obtained through forest inventory methods with remote sensing data, researchers and practitioners can gain comprehensive insights into various aspects of forest ecosystems.
Land, a finite and vital resource for the economic advancement of nations, faces increasing strain due to population growth. The dynamic condition of land requires immediate attention. Understanding both land use and land cover is paramount for grasping the connection between

human actions and the environment, crucial for preventing forest degradation (Dimyati *et al*., 1996) [7]. Change detection involves identifying differences in the state of an object or phenomenon over time and is essential for understanding the dynamic relationship between human societies and nature. It's important to note that alterations in land use/land cover patterns do not always signify negative changes, such as forest loss due to deforestation. They can also indicate positive changes, like forest expansion, increased water bodies, or expanded plantations (Panigrahy *et al*., 2010) [19]. Changes in classification may also involve instances where forest cover is not detected due to factors like cloud cover, reduced reflectance caused by leaf fall, or poor image quality.

The spectral reflectance from vegetation offers valuable information about the structure and composition of forest stands. Tree volume refers to the amount of wood present in an individual tree, while stand volume refers to the total amount of wood present in the entire forest stand (Lehtonen *et al*., 2004) [12]. Advancements in remote sensing technologies, particularly through the use of high-resolution satellite imagery, have significantly expanded the capabilities for monitoring forest ecosystems. These technologies provide accurate and detailed measurements of key forest attributes such as canopy cover, vegetation density, tree species distribution, and biomass. The ability to track these changes, whether related to deforestation, forest degradation, or recovery, is crucial for improving our understanding of forest dynamics and trends.

Materials and Methodology

Study area

The present study was focused on various forest types within the Yellapur Forest Division in Uttara Kannada District. Located in the eastern part of the district, the Yellapur Forest Division covers a total area of 168,986.66 hectares, including Betta lands (protected forests), which represents 86.97% of the division's geographical area (1,902.28 km²). The division is bounded by longitudes 74°25' to 75°6' East and latitudes 14°44' to 15°7' North. The study area is depicted in Figure 1. The Yellapur Forest Division encompasses three distinct forest types *viz* dry deciduous, moist deciduous and semi-evergreen.

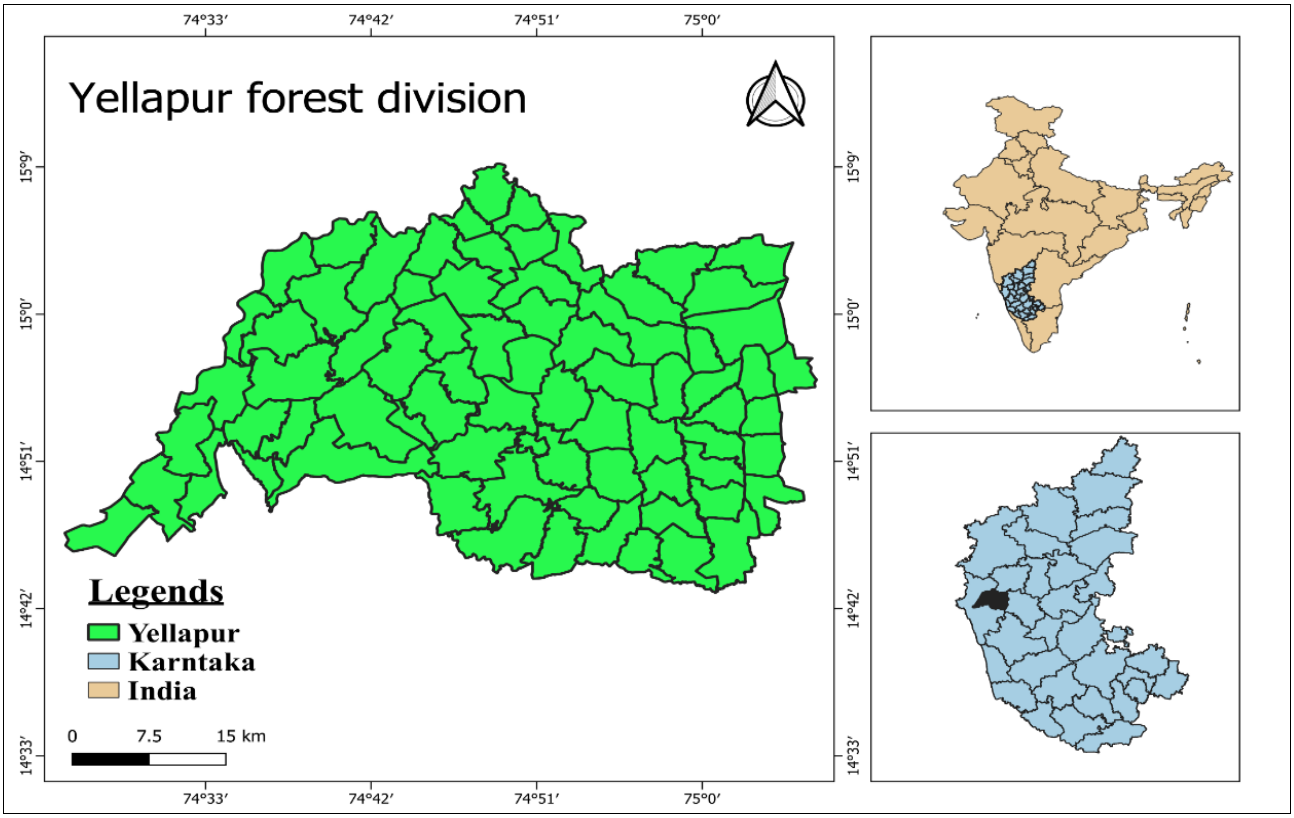

Fig 1: Study Area map

Experimental Details

For conducting the experiment, satellite images of the Yellapur area for different years were used. The ground truth data was collected based on the forest density classes. Forest inventory was done for biomass and carbon studies. The experiment are as follows (Fig. 2).

Shapefile of Yellapur forest division

A shapefile of the Yellapur forest division includes dry deciduous, moist deciduous and semi-evergreen. It is used to represent geographical features, such as points, lines and polygons, along with their associated attributes. A shapefile is a collection of several files with different extensions, where the primary file stores the geometric data, while other associated files store spatial indices, attribute data and projection information.

Satellite data

Satellite imagery is collected from Landsat 7 for the years 2000 and 2010 (Tables 1). and Landsat 8 for 2023 (Tables 2). Landsat is a series of Earth-observing satellite missions jointly managed by NASA and the U.S. Geological Survey (USGS). The data provides multispectral images of the Earth's surface. These images serve as the primary data source for analyzing changes in land cover over the selected years.

Table 1: Details of Landsat 7 sattellite data

Launch date	April 15th 1999
Swath width	185 km
Repeat cycle	16 days
Scene size	170 kilometres north-south by 185 kilometres east-west, or 106 miles by 115 miles
Resolution (m)	Panchromatic band: 15 meters Visible (VIS), near-infrared (NIR) and shortwave infrared (SWIR): 30 meters Thermal infrared: 60 meters
Sensor	Enhanced Thematic Mapper Plus (ETM+)

Table 2: Details of Landsat 8 sattellite data

Launch date	Feb 2013
Swath width	185 km
Repeat cycle	16 days
Scene size	185 kilometres cross track by 180 km long
Resolution (m)	Panchromatic band: 15 meters Visible (VIS), near-infrared (NIR) and shortwave infrared (SWIR): 30 meters Thermal infrared: 100 meters
Sensor	Operational land Imager (OLI) and the Thermal Infrared Sensor (TIRS)

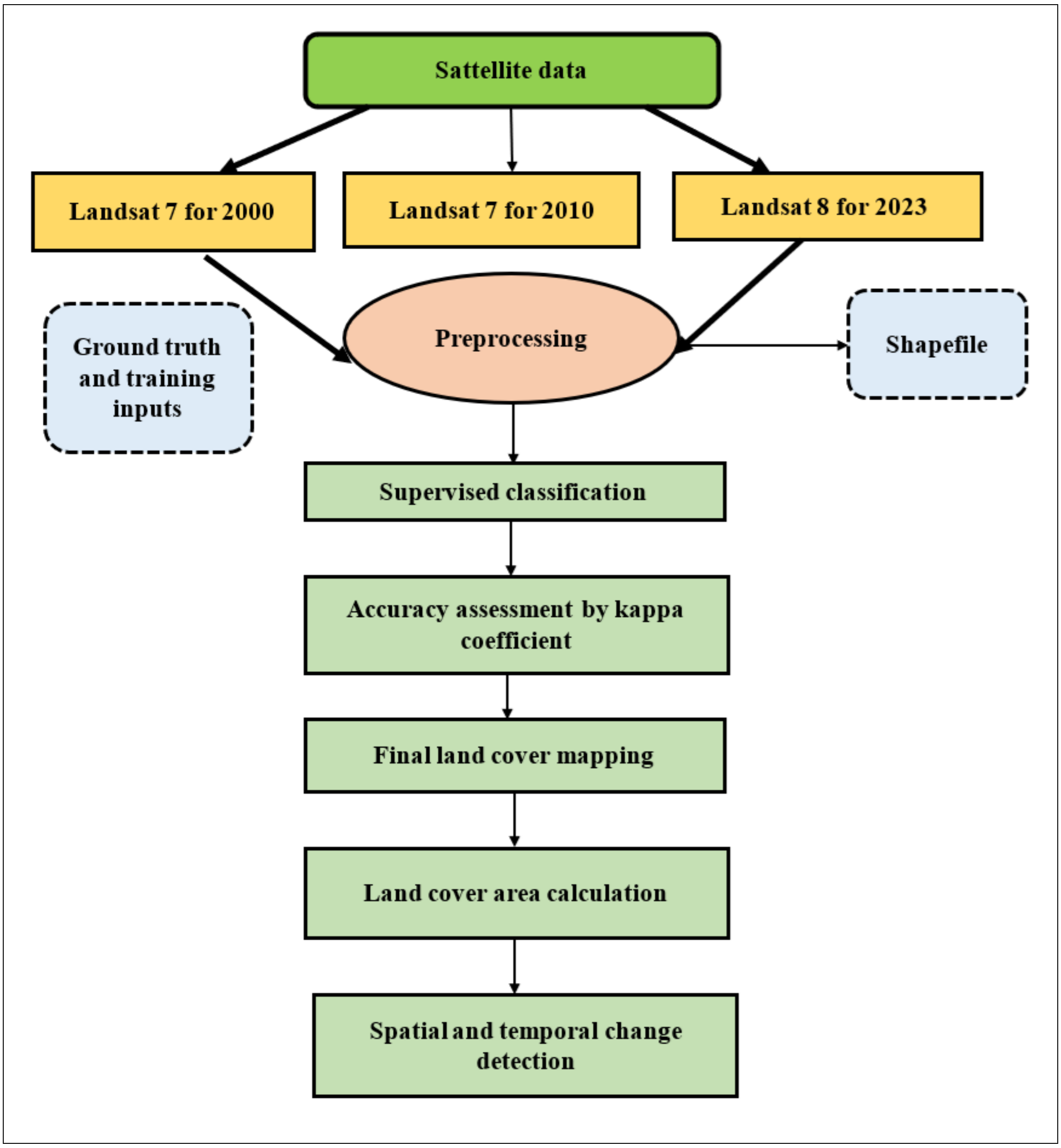

Fig 2: Flow chat of methodology of spatial and temporal changes of Yellapur forest division

Ground truth and training inputs

This involves collecting accurate, on-site information about the land cover types present in the study area. Ground truth data can be obtained through field surveys, aerial photography, or existing maps. Training Inputs are the sample data points used to train the classification based on the maximum likelihood algorithm. They consist of known land cover types that the algorithm will use to learn and recognize patterns in the satellite imagery. Ground truth and training inputs are essential for ensuring the classification model accurately identifies different land cover types such as,

Vegetation: Areas covered with trees and shrubs.

Built-up: areas including cities and towns.

Water Bodies: Rivers, lakes and other water features.

Agriculture land: The land under cultivation.

Preprocessing

Preprocessing ensures that the satellite data is accurate, consistent and ready for further analysis. Preprocessing involves various steps to prepare the raw satellite data for analysis. These steps include:

Radiometric Correction: Adjusts the sensor's recorded values to true reflectance values, correcting for sensor noise and inconsistencies.

Geometric Correction: Ensures that the satellite images align correctly with geographical coordinates. This involves correcting for distortions due to the Earth's curvature, satellite motion and sensor angle.

Cloud Removal: Clouds and their shadows can obscure land cover features, so they are identified and masked out from the images.

Image Enhancement: Techniques like contrast stretching, edge enhancement and filtering are applied to improve the visibility of features of interest.

Calculation of vegetation index (NDVI)

Normalized Difference Vegetation Index (NDVI) is used to quantify vegetation health and cover. NDVI is calculated using the red and near-infrared bands of the spectrum of multispectral sensor of Sentinel-2. The Normalized Difference Vegetation Index (NDVI) is a widely used vegetation index that is calculated using the red and near-infrared (NIR) bands of satellite imagery. The formula for NDVI is:

$$NDVI = (NIR-RED)/(NIR + RED) = (B8 - B4) / (B8 + B4)$$

Supervised classification

Using the ground truth and training inputs, a supervised classification algorithm (Maximum Likelihood) is trained to recognize and categorize different land cover types. The algorithm assigns each pixel in the satellite image to a specific land cover class based on the patterns and characteristics learned from the training data. Maximum Likelihood Classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. The result is a classified image where each pixel is labelled with a land cover type.

Final land use land cover map

Based on the results of the supervised classification and accuracy assessment, the final land cover map is produced. This map visually represents the spatial distribution of different land cover types for the study years. The map is validated against additional ground truth data or other independent datasets to ensure its accuracy and reliability.

Land cover area calculation

The area covered by each land cover type is calculated from the final land cover map. This involves summing the pixel areas for each class and converting them into meaningful units (hectares). This step provides quantitative information on the extent of different land cover types, which is crucial for various applications like resource management, environmental monitoring and urban planning.

Spatial and Temporal Change Detection

By comparing land cover maps from different years (2000, 2010 and 2023), changes in land cover are detected. This involves identifying areas where significant changes have occurred, such as deforestation, urban expansion, or changes in water bodies.
Spatial change detection examines the geographic location and extent of changes, while temporal change detection analyses how these changes have evolved over time. The results provide insights into land use dynamics, environmental impacts and trends, helping inform policy decisions, conservation efforts and sustainable development planning. This analysis helps in understanding.

- **Deforestation:** Identifying areas where forest cover has decreased.
- **Urbanization:** Monitoring the expansion of urban areas.
- **Agricultural Changes:** Tracking changes in crop patterns or farmland.
- **Water Bodies:** Observing changes in the extent of lakes, rivers and wetlands.

Accuracy assessment by Kappa coefficient

Accuracy assessment evaluates the performance of the classification algorithm. The kappa coefficient is a statistical measure that compares the observed accuracy with the expected accuracy (random chance) and provides a value between -1 and 1, where 1 indicates perfect agreement and values ≤ 0 indicates no agreement.

$K = (ND - P)/(N^2 - P)$

K= kappa coefficient

D= Sum of correctly classified class pixels

P= Sum of the product of row total and column total

N= Total number of pixels

Experimental results

The spatial and temporal change in the Yellapur forest division of Uttara Kannada over 23 years i.e. 2000 to 2023 was assessed using Landsat 7 Landsat 8 satellite image with 30 m spatial resolution. The results of the experiment are mentioned below.

Normalized Difference Vegetation Index for different years in Yellapur forest division of Uttar Kannada

NDVI values were derived for various land use and land cover (LULC) types over different years using the RED and NIR bands from Landsat 7 and Landsat 8 imagery. Landsat 7 for the years 200 and 2010 has a total of 8 bands, with band 3 (red) and band 4 (NIR) and Landsat 8 for the year 2023 has 11 bands with band 4 (RED) and band 5 (NIR) were used for NDVI calculation. The NDVI values ranged from -0.33 to +0.88 for the year 2000 (Fig. 3), 0.17 to +0.76 for 2010 (Fig. 4) and -0.07 to +0.70 for 2023 (Fig. 5). These differences show varying levels of vegetation health and thickness. Higher values mean healthier vegetation and lower values indicate the water body. These changes are linked to factors like urban growth, deforestation and farming activities.

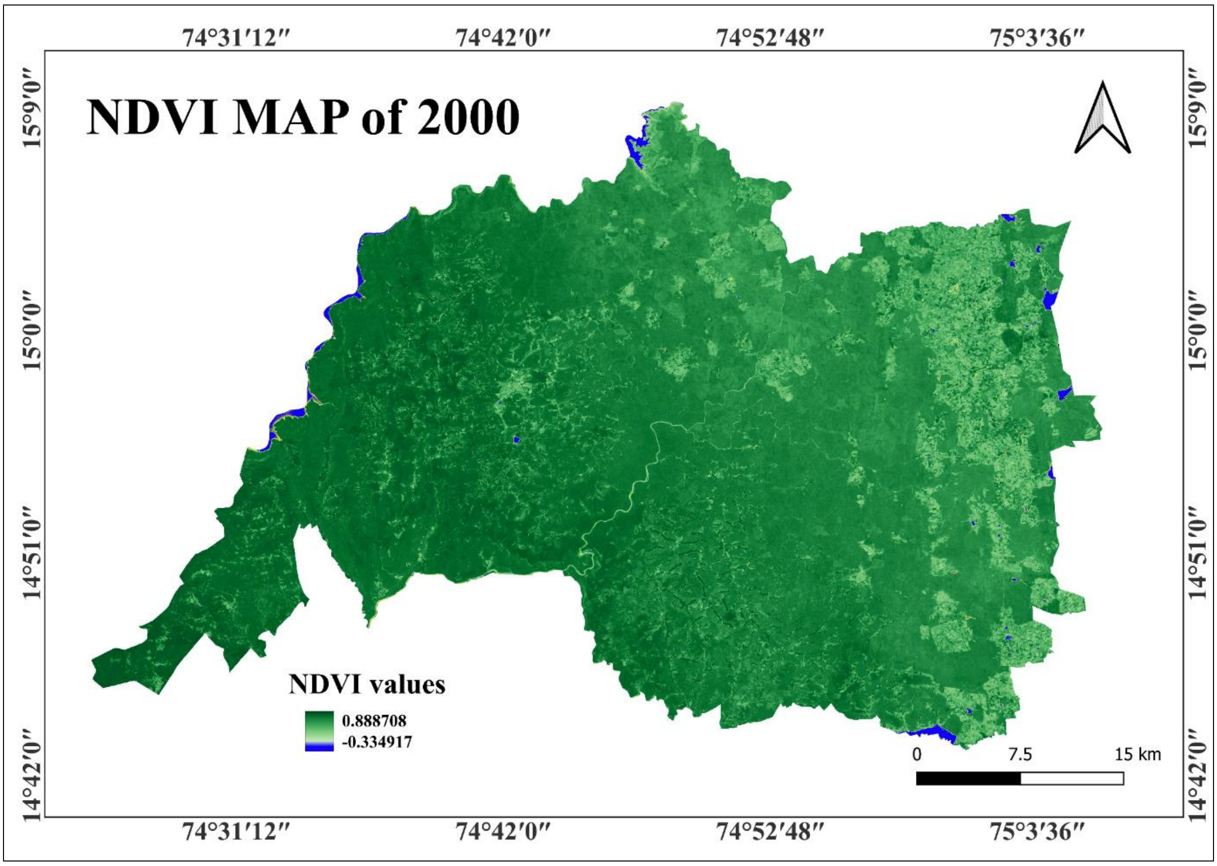

Fig 3: NDVI map of Yellapur forest division for the year 2000

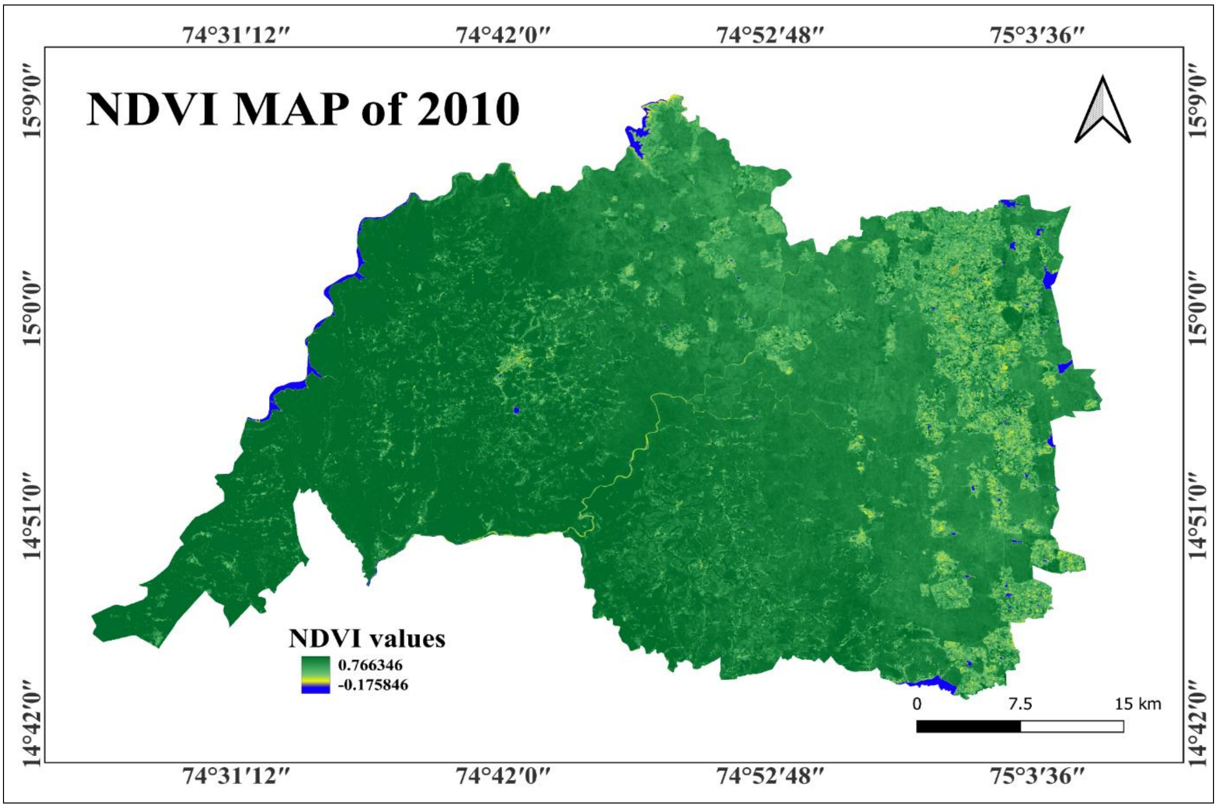

Fig 4: NDVI map of Yellapur forest division for the year 2010

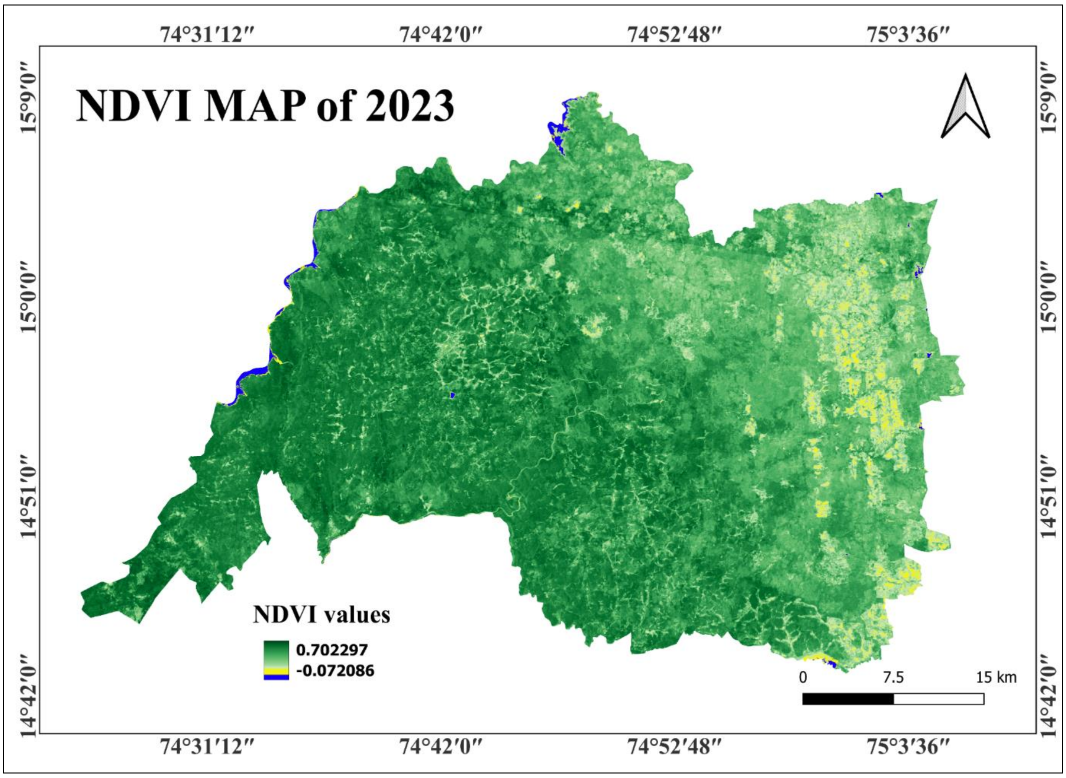

Fig 5: NDVI map of Yellapur forest division for the year 2023

Area under different land use land cover Classes of Yellapur forest division for the year 2000: A detailed study of Land Use Land Cover (LULC) using Landsat-7 data for 2000, offered valuable insights into the distribution and range of different land cover types within the Yellapur forest division. Vegetation emerged as the dominant land cover, encompassing 178,108 hectares constituting 90.35 per cent of the total area including forests, plantations and other green spaces that are vital for ecological balance and biodiversity. Agricultural land covering 12,369 hectares is 6.27 per cent of the area. Built-up areas account for 4,564 hectares (2.32%) of the land. Water bodies including lakes, ponds and rivers are the smallest land cover category occupying 2,087 hectares indicating 1.06 per cent of the area (Table 3). The total area under the Yellapur forest division is 197,130 hectares. The LULC map of the Yellapur forest division is depicted in Figure 6.

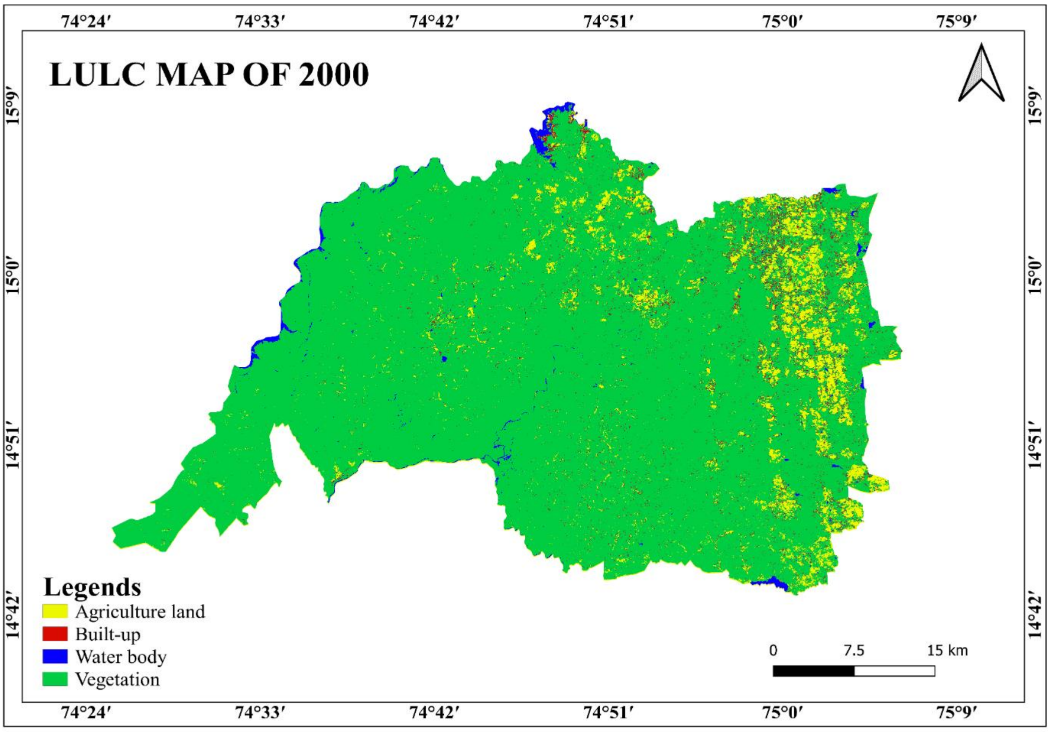

Fig 6: LULC map of Yellapur forest division for the year 2000

Table 3: The area under different land use and land cover classes of Yellapur forest division for the year 2000

Sl. No.	LULC Classes	Area (ha)	Area (%)
1	Agriculture land	12,369	6.27
2	Built-ups	4,564	2.32
3	Waterbody	2,087	1.06
4	Vegetation	1,78,108	90.35
Total		1,97,130	100

Area under different land use land cover Classes of Yellapur forest division for the year 2010

The Land Use Land Cover (LULC) analysis using Landsat-7 data for 2010 provided the distribution and extent of various land cover categories within the study area. Vegetation emerged as the dominant land cover encompassing 1,65,832 hectares constituting 84.12 per cent of the total area including forests, plantations and other green spaces that are vital for ecological balance and biodiversity. Built-up areas account for 15,073 hectares representing 7.65 per cent of the land. Agricultural land covers 14,224 hectares (7.22%) of the area. Water bodies including lakes, ponds and rivers are the smallest land cover category occupying 2,000 hectares which is 1.01 per cent of the area (Table 4). The total area under the Yellapur forest division is 197,130 hectares. The LULC map of the Yellapur forest division is depicted in Figure 7.

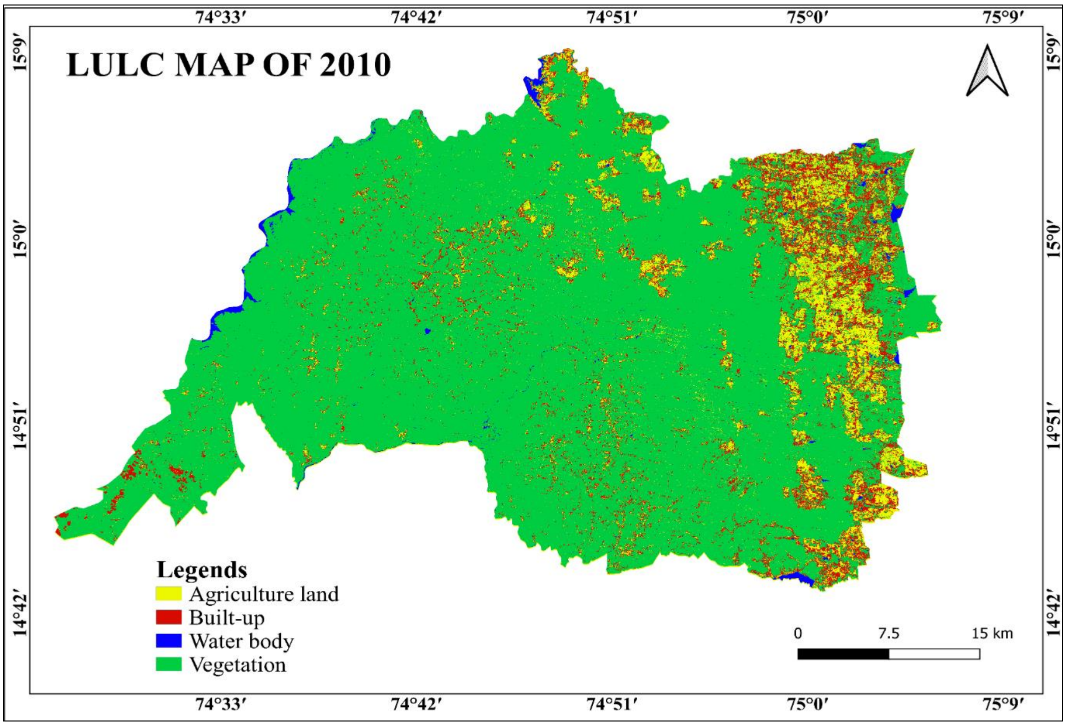

Fig 7: LULC map of Yellapur forest division for the year 2010

Table 4: The area under different land use and land cover classes of Yellapur forest division for the year 2010

Sl.No.	Lulc Classes	Area (ha)	Area (%)
1	Agriculture land	14,224	7.22
2	Built-ups	15,073	7.65
3	Waterbody	2000	1.01
4	Vegetation	1,65,832	84.12
Total		1,97,130	100

The area under different land use land cover Classes of Yellapur forest division for the year 2023

An extensive Land Use Land Cover (LULC) analysis using Landsat-8 data from 2023 indicating various LULC classes *Viz.* vegetation covers an area of 1,61,976 hectares (81.68%) including forests, plantations and other green spaces that are vital for ecological balance and biodiversity. Built-up areas account for 17,413 hectares representing 8.83 per cent of the land. Agricultural land covers 16,976 hectares which is 8.61 per cent of the area. Water bodies including lakes, ponds and rivers are the smallest land cover category occupying 1,721 hectares which is 0.87 per cent of the area (Table 5). The total area under the Yellapur forest division totals 197,130 hectares. The LULC map of the Yellapur forest division is depicted in Figure 8.

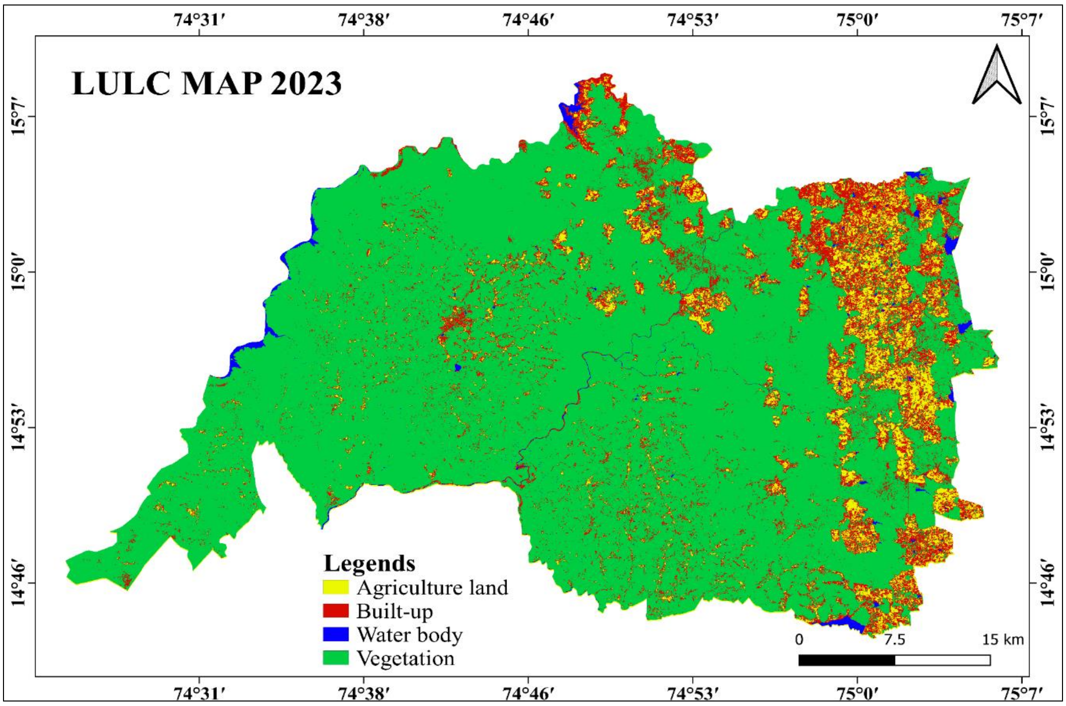

Fig 8: LULC map of Yellapur forest division for the year 2023

Table 5: The area under different land use and land cover classes of Yellapur forest division for the year 2023

Sl. No.	LULC Classes	Area (ha)	Area (%)
1	Agriculture land	16,976	8.61
2	Built-ups	17,413	8.83
3	Waterbody	1,721	0.87
4	Vegetation	1,61,018	81.68
Total		1,97,130	100

Land use land cover change between 2000 and 2023 in the Yellapur forest division

The distributed area of each land use and land cover change between 2000 and 2023 was analysed. It was observed that the area under vegetation in 2000 was 178,108 hectares (90.35%) was reduced to 165,832 hectares (84.12%) in 2010. It further decreased to 160,018 hectares (81.68%) in the year 2023. The percentage reduction in vegetation area over 23 years was 8.67 per cent (Table 6). The reason for the reduction is mainly deforestation, agriculture expansion and infrastructure development.

The area of agricultural land was 12,369 hectares in 2000 (6.27%). By 2010, this area had increased to 14,224 hectares (7.22%). In the year 2023, the area under agricultural land further increased to 16,976 hectares (8.61%). The per cent increase in agricultural land over 23 years was 2.34. primarily due to the rise in population and the growing demand for food.

The area under built-up was 4,564 hectares in the year 2000, accounting for approximately 2.32 per cent of the total geographical area of Yellapur. By 2010, this area had increased to 15,073 hectares (7.65%). In the year 2023, the built-up area further expanded to 17,413 hectares representing about 8.83 per cent of the total area. The percentage increase over the 23 years from 2000 to 2023 was 6.51 per cent, primarily due to urbanization, infrastructure development and increased habitation (Table 6).

The area covered by water bodies, including lakes, rivers and ponds was 2,087 hectares in 2000 accounting for 1.06 per cent of the total geographical area. In the year 2010, the area under water bodies decreased to 2,000 hectares (1.01%) which further decreased to 1,721 hectares (0.87%) in the year 2023. Over the 23 years from 2000 to 2023, the percentage of area covered by water bodies decreased by 0.91 per cent, primarily due to the conversion of land to agricultural fields.

Over 23 years from 2000 to 2023 in Yellapur forest division the forest cover lost was around 17090 ha on the other hand there is an increase in agricultural land of about 4607 ha. whereas an increase in the built-up area was 12849 ha due to urbanization, agriculture expansion and deforestation.

Table 6: The land use land cover change of Yellapur forest division over 23 years from 2000-2023

LULC/Year	2000	Per cent area (2000)	2010	Per cent area (2010)	2023	Per cent area (2023)	Change (%)
Agricultural land	12,369	6.27	14,224	7.22	16,976	8.61	2.34
Built-ups	4,564	2.32	15,073	7.65	17,413	8.83	7.03
Waterbody	2,087	1.06	2000	1.01	1,721	0.87	-0.19
Vegetation	1,78,108	90.35	1,65,832	84.12	1,61,018	81.68	-8.67
Total	1,97,130	100	1,97,130	100	1,97,130	100	

Change detection of LULC in the Yellapur forest division from 2000 to 2023

The significant land use and land cover changes among the 16 classes are detailed in (Table 7 and Fig 9) revealing significant shifts in land categories. A considerable portion of land changed, transitioning between agriculture, built-up areas, water bodies and vegetation. Large areas of agricultural land have been converted to built-up areas, while some vegetation has also been lost to urban expansion. Additionally, there has been a noticeable shift from water bodies and vegetation to other land use types reflecting the ongoing impacts of human activity on the landscape.

The major findings show that about 901.01 hectares of built-up land changed to agricultural land, while 5,263.92 hectares of vegetation were turned into farmland. A large shift occurred with 15,784.92 hectares of vegetation being converted into built-up areas and 4,904.19 hectares of agricultural land also converted to built-up areas. On the other hand, around 2,420.82 hectares of farmland were converted back to vegetation. These changes reflect the ongoing shifts in land use influenced by urban growth, infrastructure development and the expansion of agriculture (Table 8 and Fig. 10).

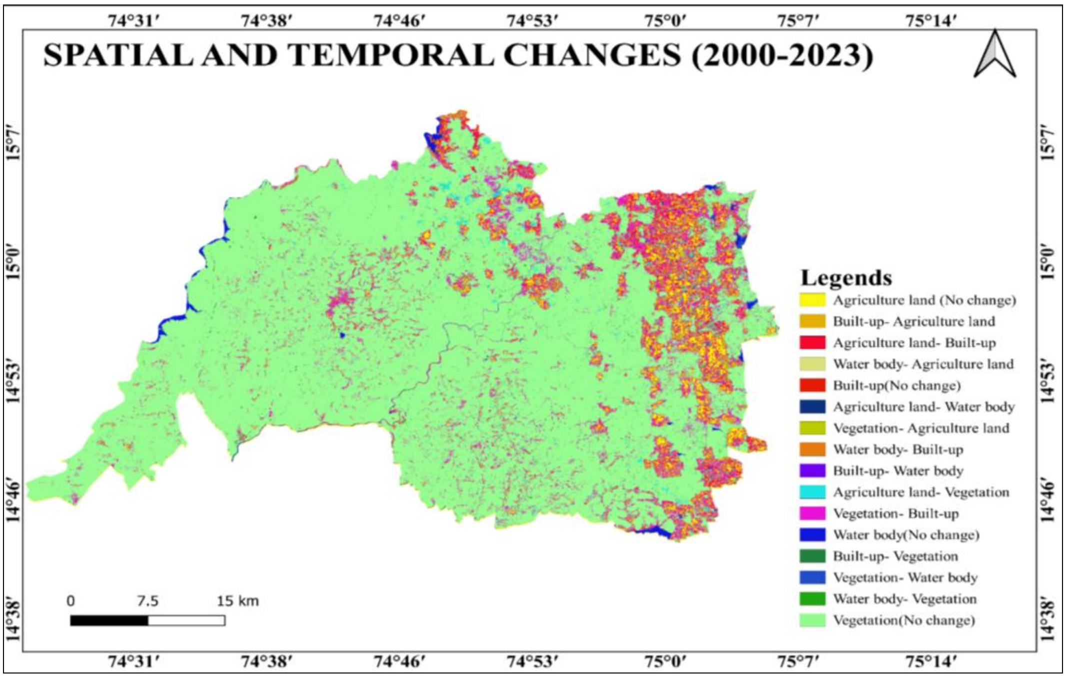

Fig 9: Spatial and temporal change map of Yellapur forest division (2000-2023)

4.2.7 Accuracy assessment

An accuracy evaluation was carried out in Google Earth Engine using the. Confusion Matrix () function. The overall accuracy and kappa coefficient were calculated using the. Accuracy () and. kappa () functions, respectively. In 2000, the overall accuracy was recorded at 96.07 per cent, with a Kappa coefficient of 0.92. In 2010, the overall accuracy was 95.29 per cent and the Kappa coefficient was 0.91. By 2023, the overall accuracy reached 95.45 per cent, with a Kappa coefficient of 0.94. These values reflect the observed accuracy and agreement measures for the respective years (Table 9).

Table 7: The area under different land use and land cover change in Yellapur forest division over 23 years from 2000-2023

Sl. No.	Land cover Land cover change	Area(ha)
1	Agriculture land (No change)	5804.19
2	Built-ups to Agriculture land	0
3	Waterbody to Agriculture land	31.05
4	Vegetation to Agricultural land	5263.92
5	Agriculture land to Built-ups	4904.19
6	built-ups (No change)	1896.48
7	Waterbody to Built-ups	458.91
8	Vegetation to Built-ups	15784.92
9	Agriculture to Waterbody	30.78
10	Built-ups to Waterbody	10.08
11	Waterbody (No Change)	1157.67
12	Vegetation to Waterbody	591.75
13	Agriculture land to Vegetation	2420.82
14	Built-ups to Vegetation	1739.7
15	Waterbody to Vegetation	269.19
16	Vegetation (No change)	157863.8

Table 8: The area under Major land use and land cover change in Yellapur forest division over 23 years from 2000-2023

Sl. No.	Land Cover Change	Area(ha)
1	Built-ups to Agricultural land	908.01
2	Vegetation to agricultural land	5263.92
3	Agricultural land to Built-ups	4904.19
4	Vegetation to Built-ups	15784.92
5	Agricultural land to Vegetation	2420.82

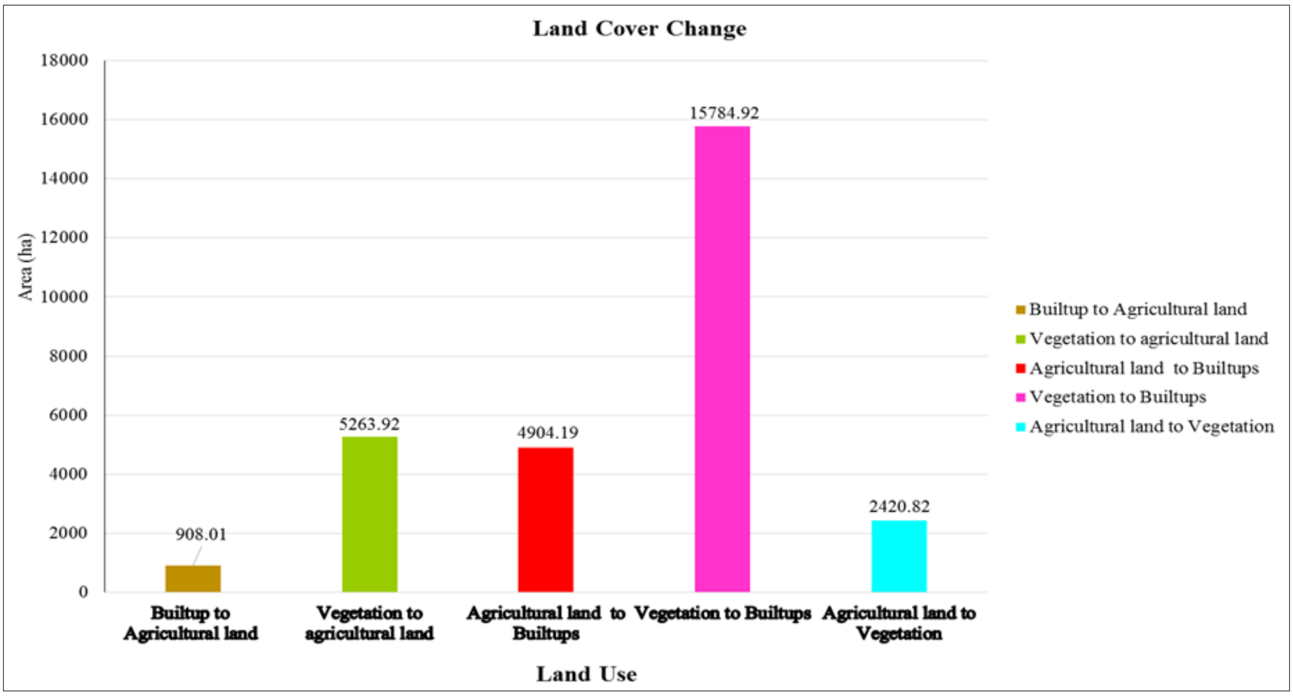

Fig 10: Detection of major changes in different land use classes

Table 9: The overall accuracy and Kappa coefficient of LULC mapping of the Yellapur forest division for different years

Sl. No.	Year	Overall accuracy (%)	Kappa coefficient
1	2000	96.07	0.92
2	2010	95.29	0.91
3	2023	95.45	0.94

Discussion

From 2000 to 2023, the Yellapur Forest Division has experienced significant land use and land cover changes primarily due to urbanization, agricultural expansion and infrastructure development. Rapid population growth and economic activities in the region have led to the encroachment of forested areas for the development of built-up zones, particularly for residential and industrial purposes. A considerable portion of the forest cover has been cleared to make way for agricultural land as farmers seek to meet the rising demand for food production. Infrastructure projects such as road construction and the establishment of power lines have further fragmented the forest landscape contributing to the degradation of natural habitats. Resource extraction including logging and the collection of non-timber forest products has also played a role in reducing forest cover. These pressures have led to a significant decrease in vegetation and biodiversity while the built-up and agricultural lands have steadily increased in the Yellapur Forest Division during these 23 years.

Similar finding was reported by Roy *et al*. (2015) [22] conducted a decadal change detection analysis spanning from 1985 to 2005 reveal a continuous decline in forested land, accompanied by an increase in croplands and built-up areas. This shift has led to degradation, desertification and biodiversity loss, influenced by both physical and human factors. The study also enhances our understanding of how land use and land cover (LULC) changes are linked to climate change, food production, health, urbanization, coastal zone management and transboundary migration. Additionally, the maps generated from this analysis will help identify areas vulnerable to land degradation, changing precipitation and temperature patterns and shifts in biome boundaries. Bhat *et al*. (2017) [5] conducted a similar study and highlighted the significant environmental impacts of current urban growth trends on surrounding ecosystems. The rapid expansion of urban and built-up areas has led to dramatic shifts in land use and land cover marked by sharp declines in agricultural lands, fallow areas and vacant spaces. The challenges posed by a densely populated area with high resource consumption and limited land availability have severely affected the city's ability to address the demands of modern growth. To tackle these issues, it is crucial to develop planning policies that promote a sustainable environment. Rational urban planning strategies should be implemented to mitigate the negative effects.

Summary and Conclusion

Remote sensing and GIS tools provide a convenient and effective means to evaluate the extent of different land cover classes and track changes in forest cover. The spatial and temporal change of forest cover assessed the change of forest cover over 23 years i.e. from 2000 to 2023 in the Yellapur forest division. Google Earth Engine and QGIS software used to assess temporal change and for map composition. The study area was classified into four different LULC classes i.e. vegetation, Built-up, Agriculture land and water body. NDVI values from Landsat 7 imagery ranged from -0.07 to +0.7 in 2000, -0.08 to +0.6 in 2010 and -0.3 to +0.8 in 2023, reflecting changes in vegetation health and density. Higher values indicate healthier vegetation, with variations influenced by urbanization, deforestation and agriculture.

In 2000, Landsat-7 data revealed that vegetation was the dominant land cover in the Yellapur forest division, spanning 178,108 hectares (90.35%), while agricultural land covered 12,369 hectares (6.27%), built-up areas 4,564 hectares (2.32%) and water bodies 2,087 hectares (1.06%). The total area of the division is 197,130 hectares. In 2010, Landsat-7 data revealed that vegetation covered 165,832 hectares (84.12%) of the Yellapur forest division, while built-up areas occupied 15,073 hectares (7.65%), agricultural land 14,224 hectares (7.22%) and water bodies 2,000 hectares (1.01%). The total area of the division is 197,130 hectares. In 2023, Landsat-8 data showed that vegetation covered 161,976 hectares (81.68%) of the Yellapur forest division, with built-up areas at 17,413 hectares (8.83%), agricultural land at 16,976 hectares (8.61%) and water bodies at 1,721 hectares (0.87%). The total area of the division is 197,130 hectares. From 2000 to 2023, significant land use changes included 15,784.92 hectares of vegetation converted to built-up areas and 5,263.92 hectares of vegetation to agricultural land. Additionally, 4,904.19 hectares of agricultural land transitioned to built-up areas, reflecting major shifts in land use.

The LULC mapping for the Yellapur Forest Division demonstrates reliable classification, with an overall accuracy of 96.07 per cent and a Kappa coefficient of 0.92 in 2000, a slight decline to 95.29 per cent accuracy and 0.91 Kappa in 2010 and a recovery to 95.45 per cent accuracy and an improved Kappa of 0.94 in 2023, indicating consistently high acceptance of the classification throughout the years.

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