# A SPATIO-TEMPORAL ANALYSIS OF URBAN EXPANSION AND ITS IMPACT ON LAND USE/LAND COVER DYNAMICS

A DISSERTATION

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MAY 2023

# <u>CANDIDATE'S DECLARATION</u>

I, Utkarsh, Roll No. 2K20/GEO/08 of M. Tech Geoinformatics Engineering, hereby declare that the project dissertation titled **"A Spatio-temporal Analysis of Urban Expansion and its Impact on Land Use Land Cover Dynamics"**, which is submitted by me to the Department of Civil Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has previously not formed the basis for the award of any degree, diploma, associateship, fellowship, or other similar title recognition.

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# CERTIFICATE

I hereby certify that the Project Dissertation titled **"A Spatio-temporal Analysis of Urban Expansion and its Impact on Land Use and Land Cover Dynamics,"** which is submitted by Utkarsh, Roll No. 2K20/GEO/08 [Civil Engineering], Delhi Technological University, Delhi, in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision. To the best of my knowledge, this work has not been submitted in part or full for any degree or diploma to this university or elsewhere.

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# ABSTRACT

Over the past couple of decades, a significant global trend has been the rapid growth of metropolitan regions, with profound implications for land use, environmental sustainability, and socio-economic development. In this context, the spatiotemporal analysis of urban expansion using Land Use/Land Cover (LULC) data has emerged as a crucial research area for understanding the dynamics of urbanization, evaluating the impacts of urbanization on the environment and human well-being, and informing effective urban planning and management strategies.

This study aims to contribute to this field by investigating the spatiotemporal patterns and trends of urban expansion in a specified area over a certain period using LULC data. This study utilizes remotely sensed data and Geographic Information System (GIS) techniques to extract LULC data and analyze the change in urban areas. The analysis includes *Image Classification* of Landsat and Sentinel data, which are used to derive the LULC data of the region of interest, and then change detection is carried out among the different temporal data gathered to describe the spatial pattern of urban areas.

Applications involving Land Use and Land Cover benefit greatly from change detection. It includes urban expansion, cultivation, and landscape changes. The aim of the study is to examine the underlying trends of land use and land cover change in the city of Patna, situated in the state of Bihar, covering a period of several years, ranging between two separate decades. The results of the analysis would unearth urban expansion's spatiotemporal dynamics, showing where and when urbanization occurred, how the urban form changed, and how the landscape was transformed. The study also identifies the factors driving urban expansion, such as population growth, economic development, and urban policy, and assesses the impacts of urbanization on the environment and socio-economic conditions.

The results of the research made in this study would have significant implications for urban planning and management. The output will provide insightful details into the spatiotemporal characteristics of urban expansion, which can inform the development of effective strategies for controlling urban growth and alleviating its obstructive impacts. This research focuses attention to the worth of incorporating spatiotemporal analysis into urban planning and management practices and underscores the utility of LULC data for understanding the dynamics of urbanization.

Overall, this study contributes to the ongoing efforts to create more sustainable, resilient, and habitable urban environments amid rapid urbanization globally.

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**UTKARSH**

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## LIST OF ABBREVIATIONS

| | |
|---|---|
| CM | Confusion Matrix |
| CRS | Coordinate Reference System |
| DEM | Digital Elevation Model |
| ESA | European Space Agency |
| ETM | Enhanced Thematic Mapper |
| FCC | False Color Composite |
| GCP | Ground Control Points |
| GIS | Geographic Information System |
| GRP | Ground Reference Points |
| IC | Image Classification |
| JPEG | Joint Photographic Experts Group |
| KC | Kappa Coefficient |
| LiDAR | Light Detection and Ranging |
| LULC | Land Use Land Cover |
| NASA | National Aeronautics and Space Agency |
| NCC | Natural Color Composite |
| OLI | Operational Land Manager |
| PUA | Patna Urban Agglomeration |
| RGB | Red Green Blue |
| RS | Remote Sensing |
| TIFF | Tag Image File Format |

| | |
|---|---|
| TIRS | Thermal Infrared Sensor |
| USGS | United States Geological Survey |
| UTM | Universal Transverse Mercator |
| WGS1984 | World Geodetic System 1984 |

***CHAPTER 1***

# ***INTRODUCTION***

## 1.1 MOTIVATION

More than half of the world lives in urban areas, and by 2050, it has been estimated that the proportion is set to increase to around sixty-five percent of the planet's population [1], and the numbers are going to exceed 9.3 billion [2]. According to these estimates, two and a half billion people are going to be added to the world population, and almost ninety percent of these increased numbers are expected to be living in urban areas of underdeveloped or developing countries [3]. This increase in population will be accompanied by an increase in urban areas, resulting in urban expansion. Changing Land Use & Land Cover (LULC) because of increased needs leads to urban expansion.

The world population has seen a rapid increase since the18th century post *Industrial Revolution*, and the population seems to be accumulating in certain centers that are being developed as urban areas. Therefore, observing, planning, and modeling the urban expansion of the cities is a key aspect to be considered for necessary actions.

Urbanization is a reform that simultaneously involves variation in population, economy, and land cover [4]. In tandem with notable population migration and economic expansion, extensive or immense tracts of agricultural land have been lost to or converted into urban areas, leading to massive urbanization. Urban expansion can also be one of the reasons for aggravated heat effects on urban land. Thus, it is vital to understand the urban expansion process, for urban planning and management to develop sustainable cities.

The change in LULC of a region is a consequence of socio-economic and natural variables and the actions of humans in real time. The changes in LULC are mainly affected by the increase or decrease in population growth rate of the land [5]. Land use change is an ancient phenomenon implying to the way mankind utilizes the land.

Change detection related to LULC detects changes in urban expansion, cultivation, and landscape changes [6]. Geographic Information System (GIS) and Remote Sensing (RS) are dominant and affordable tools for evaluating the spatial & temporal changes from LULC images [7]. Remote Sensing data is useful and essential for detecting change in land use and land cover research.

Hence, the purpose of this research is to analyze the pattern or current shift of land use and land cover in the district of Patna, situated in the state of Bihar. Patna is the *5th* fastest flourishing urban city in India and the *21st* fastest expanding city in the world. In this research, LULC changes have been probed in by means of remotely sensed data and GIS tools, using *ArcGIS Pro* software. We anticipate that the findings of this research would contribute to sustainable and long-term development.

## 1.2 BACKGROUND

Urban expansion is a pervasive phenomenon that has been accelerating at an unparalleled rate in past few decades. It is driven by a variety of reasons such as exponential rise in population, economic development, and changing land use patterns. The expansion of urban areas has profound implications on various aspects of society, including land use planning, infrastructure development, environmental sustainability, and socio-economic well-being.

As urban areas expand, they encroach upon previously undeveloped or agricultural lands, leading to changes in land use and land cover. These variations can have far-reaching repercussions on ecosystems and climate patterns. Urban expansion also poses challenges in terms of infrastructure provision, transportation, housing, and social services.

Understanding and managing urban expansion is crucial for sustainable development and the well-being of urban residents. Effective urban planning requires accurate and current intel on the extent, patterns, and factors of urban augmentation. This is where the application of Land Use and Land Cover (LULC) analysis and the change detection techniques play a significant role.

LULC analysis involves the stratification and mapping of different land cover types within an area, like developed regions, plantation, water bodies, and agricultural lands.

## 1.3 PROBLEM STATEMENT

Monitoring the transformation of LULC has its own significance because of the impacts they create on climate, economy, and living beings. Despite the availability of remotely sensed data and GIS technologies, accurately detecting and analyzing the differences in land use and land cover over time remains a challenge. The lack of standardized methodologies, inconsistent classification schemes, and variations in data quality and availability can lead to uncertainties and errors in LULC change detection, limiting its effectiveness for monitoring urban expansion and decision-making. Additionally, the complex interactions between natural and human systems, such as land use policy and urbanization, can make it difficult to interpret the causes and implications of LULC changes.

As a result, there is a need for further research in enhancing the accuracy, reliability, and relevance for change detection in LULC. Thus, we need to develop new approaches that can better account for the complexities and uncertainties of the changing landscape.

## 1.4 RESEARCH GAPS

Recent advancements in remote sensing technologies and data sources have enabled more accurate and detailed LULC change detection. For instance, the availability of historical satellite imagery archives has enabled the detection of long-term LULC changes, allowing for the analysis of trends and patterns over decades.

Despite the progress made in LULC change detection, several challenges still exist. One challenge is the limited availability of high-quality data in some regions, particularly in developing countries, which can limit the accuracy and reliability of LULC change detection.

Moreover, the interpretation of changes can be complex, as changes can be caused by multiple factors and can also have varying impacts. Even though there have been phenomenal changes, there are still obstacles that require attention to enhance the accurateness and reliability of LULC change detection, particularly in regions with limited data availability.

Urban expansion detection using remote sensing data often relies on a single source of data, such as satellite imagery. Future research could explore the integration of multi-source data such as aerial photography, LiDAR, and ground-based observations to improve the accuracy of urban expansion detection.

There is a lack of standardization in urban expansion detection methods, which can lead to inconsistencies and errors in results. Urban expansion is a dynamic process that can occur rapidly or gradually over time. Further research could explore methods to incorporate temporal dynamics into urban expansion detection to gain a better understanding of the tendencies and patterns of urban augmentation.

## 1.5 OBJECTIVES

The purpose of this research is to map and analyze the diversification of Land Use Land Cover (LULC) in the capital of Bihar, Patna district, with a pixel-based change detection method.

According to the literature, it is observed that there is a high demand to monitor and map LULC changes [8]. The outcomes of this study will help administer convenient perception into the LULC changes between 2002, 2013, and 2023. Furthermore, the findings of the research will help improve future planning strategies and policies for sustainable urban growth.

The objectives of the research are:

- Map the LULC of the research area with the help of multi-temporal satellite images.
- Implement a pixel-based change detection method in a GIS workflow.
- Analyze the LULC changes in the study area between 2002, 2013, and 2023.
- Perform change detection to identify the changes occurring in the urban zone of the study area.
- Highlight the spatiotemporal pattern changes of urban growth, specifically in the built-up area of the region of interest, through analyzing LULC dynamics.

## 1.6 THESIS OVERVIEW

This manuscript introduces the subject field in **Chapter 1**. The first chapter identifies the motivation behind the project, the problems faced at the commencement of the project, and the research gaps.

In **Chapter 2**, there is a detailed assessment of the project's literature and elaborated information about the study area. Crisp and precise intel about the study area have been described in this chapter.

In the next chapter, **Chapter 3**, there is a detailed description of the materials and the methods used in this project to achieve the desired results. The methodology describes the entire chronology of steps and processes involved throughout the project.

**Chapter 4** displays all the results obtained through the methods used in this project and proceeds to the discussion and analysis of the obtained results.

In the final part, i.e., in **Chapter 5**, there are concluding notes on the study's effort and its findings.

***CHAPTER 2***

***CRITICAL REVIEW***

## 2.1 LITERATURE REVIEW

### 2.1.1 Remote sensing & geographic information system

The research on urban augmentation requires quantifiable information or data about land cover classes. Remote sensing techniques can vastly help in detecting land cover pattern changes caused by brisk urban sprawl over a period because of their spatial and temporal attributes.

Land use and Land cover (LULC) change detection is a widely used application of remote sensing and Geographic Information System (GIS) technologies that enables the identification and analysis of changes taking place in the landscape over time. The exponential growth of metropolitan zones, deforestation, and agricultural land use are among the most critical land use changes affecting the environment and human well-being, making LULC change detection an important tool for understanding and managing land use dynamics.

Physical urban augmentation research necessitates both quantitative and qualitative intel with reference to classes of land cover. Various types of propositions are accessible for obtaining this data like surveys, aerial imagery or remotely sensed data [9]. Remote sensing capability can effectually detect land cover change patterns, caused by brisk urban development [10]. But because of the attributes of satellite imagery, merely utilizing remote sensing does not provide basis for further research and analysis. Therefore, GIS techniques are integrated.

The integration of GIS techniques allows us to combine and analyze satellite data using software technology [11].

The inclusion of GIS and remote sensing helps us expand our horizons. Now, we can quantify urban expansion, perform image classification and then compare the images post-classification. This will help in further identifying the causes that lead to urban expansion.

The convergence of GIS, database management, and remote sensing can help in effective monitoring and modelling urban spatial-temporal dimensions by calculating the properties of the landscape and its multiple attributes [12].

Urban expansion shows tremendous change in land cover types. Many scholars have made progressive strides towards an appropriate definition by estimating changes in Land Use and Land Cover (LULC) in urban zones [13]. This is known as change detection.

The process of identifying alterations by comparing two or more spatial-temporal images of the same region from different time frames to detect transformations of an object or phenomenon is said to be change detection [14]. Change detection techniques have been implemented for a variety of objectives, including forest and vegetation change monitoring, urban sprawl, LULC change, wetland change detection, monitoring landscape change detection, etc. [15]. These change detection algorithms are based on images from different periods of time that have been acquired through various remote sensing applications. Several strategies for change detection have been devised in the past decade, and they are broadly classified into two propositions: Object-oriented and Pixel-based [16].

The spectral differences of pixels in the same area but at different times is the main objective of pixel-based identification [17]. Whereas in object-based change detection, objects from different times are compared, such as vegetation or buildings [18]. Numerous studies have been conducted on LULC change detection using this approach of utilizing remotely sensed data and GIS techniques.

In contemporary times, the development of new remote sensing technologies and data sources, such as high-resolution satellite imagery, has enabled us to calculate more accurate and detailed LULC change detections. One popular method is the post-classification comparison method, where LULC classifications from different time periods are compared to identify changes. Despite the significant progress made in LULC change detection, there are still various issues that are required to be rectified.

One of the obstacles is the absence of organized methodologies for LULC classification and change detection. This can lead to discrepancies and errors in the analysis of LULC changes, making it arduous to collate results across separate research. This requires the development of new approaches that can better account for the complexities and uncertainties of the changing landscape.

In summary, LULC change detection is a valuable tool for understanding and managing land use dynamics and has been extensively investigated using remotely sensed data and GIS technologies.

Despite the progress made, there are still challenges that need to be addressed in order to enhance the accuracy, reliability, and relevance of LULC change detection.

### 2.1.2 Previous Research on urban sprawl through remote sensing & GIS

The augmentation of urban centers is an occurrence that is associated with the characteristics of human migration. Increase in population is one of the most consequential factors related to it. Thus, it has been previously researched by many research scholars [19].

Merely explaining divergent land cover pattern change cannot point out urban augmentation dynamics distinctly. Various earlier studies have implemented numerous urban expansion models for evaluating enlargement dynamics [20].

Anthony Vinoth Kumar, J. Pathan, S. K. and Bhanderi, R. J., 2007 have studied the spatio-temporal analysis to monitor urban growth. They targeted to investigate the urban expansion of Indore city. They utilized remote sensing and GIS techniques and Shannon entropy [21].

Singh, Ravi S., 2008 studied trends and geographical patterns of urban augmentation in Arunachal Pradesh. They inspected the behavior of urbanization. The data got collected from census of India and the territorial patterns of the region. It was discovered that urbanization in Arunachal Pradesh was frail [22].

Angela Zhu, 2010 estimates urban geography as a contributing component to trace race related violence in Paris and Marseille. This paper relied massively on qualitative data as the availability of the quantitative data was scarce because the French laws forbids census accumulation of race related data [23].

Brisk urban land cover pattern change has emerged as a significant debate in recent years because the trend of urban augmentation has unfurled all over the world, particularly in developing countries [24].

## 2.2 STUDY AREA

Patna, the capital city of Bihar, has a long and significant history dating back to ancient times (Figure 2.1). It is an ancient city that sprawls along the south banks of the holy *Ganges* River in Bihar, northeast India. Patna was established in *490 BCE* by the king of Magadh. It has rich historical, cultural, and socio-economic aspects. It was a prominent city during the Mauryan

Empire, with Patliputra (now Patna) serving as its capital. Patna is known for its rich cultural heritage. It has been influenced by various civilizations, including the Mauryan, Gupta, Mughal, and British.

Patna is an important economic center of Bihar, contributing heavily to the state's economy. It is the most populous city in the state of Bihar. The metropolitan region of Patna covers an area of around *250* square kilometers, while the entire stretch of Patna district has an estimated area of *3203* square kilometers. The city spans 25° 36' 45.64" N and 85° 9' 31.95" E, with an elevation of 55 meters (180 feet) above sea level.

Patna has undergone significant urban development in recent years. Analyzing urban planning, infrastructure projects, transportation systems, housing, and environmental sustainability efforts can shed light on the city's growth patterns and the challenges it faces as it transforms into a modern urban center. Patna is the 21$^{st}$ burgeoning urban center in the world and the 5$^{th}$ burgeoning urban zone in India, and it is anticipated to grow at an average annual rate of 3.72%.

According to the United Nations, as of 2018, Patna has a population of around 2.35 million [25], conforming it as the 19$^{th}$ biggest city in India. The current metro area population of Patna is seeing an annual growth rate of 2.02 %.

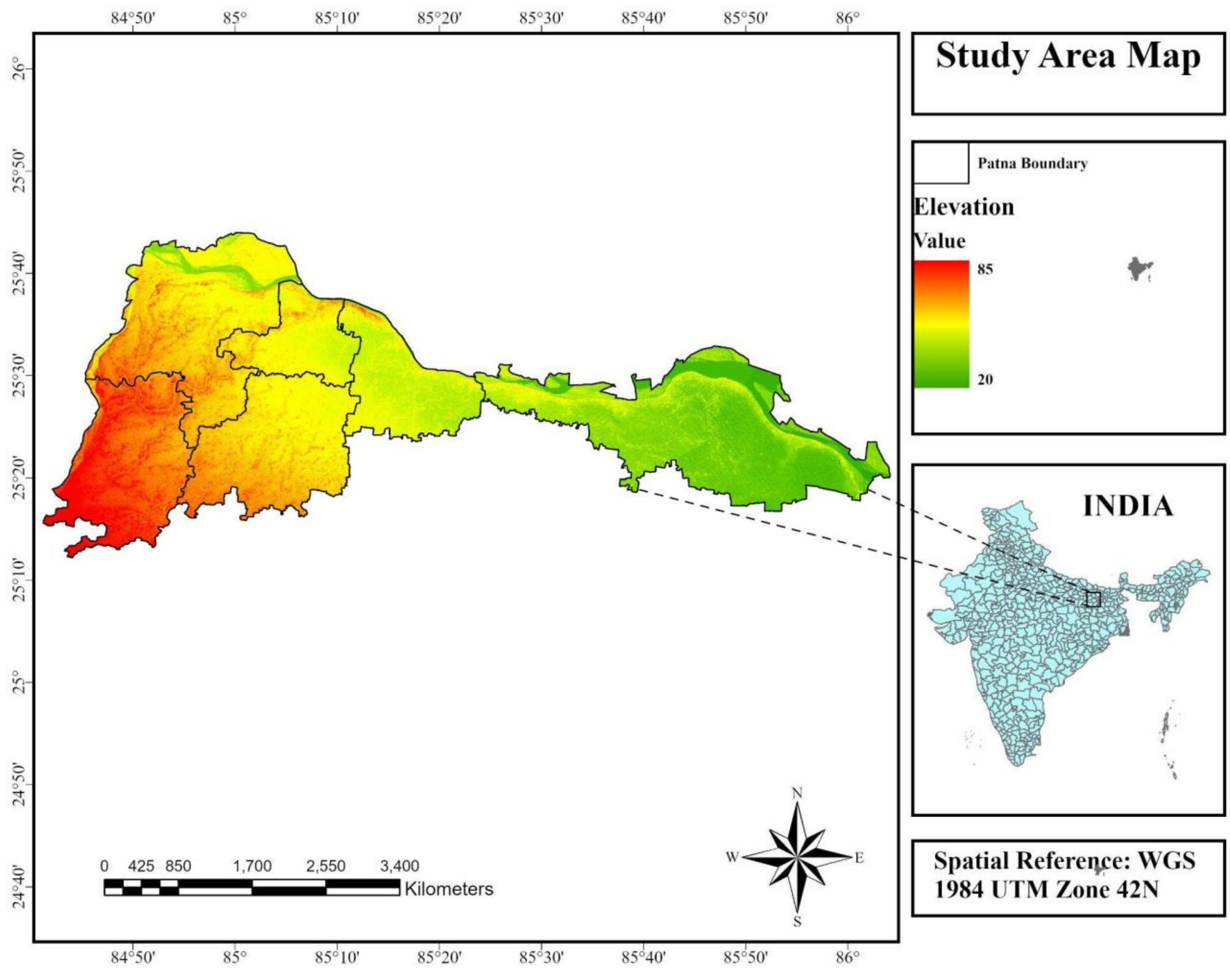


**Figure 2.1.** Study Area with elevation

Patna Urban Agglomeration (PUA) area is rapidly growing at a rate of 48.13% since the turn of the century (2001-2011), which is higher than the Patna District average growth of 30.67% and the state's average growth stands at 28% [26].

Patna district has six subdivisions. The details about the study area have been represented in Table 2.1 given below.

**Table 2.1.** Details of the Study Area (Source: https://patna.nic.in)

| Serial No. | Subdivision |
|---|---|
| 1. | Patna Sadar |
| 2. | Barh |
| 3. | Danapur |
| 4. | Patna City |
| 5. | Paliganj |
| 6. | Masaurhi |

*CHAPTER 3*

*DATA AND METHODOLOGY*

## 3.1 DATA USED

### 3.1.1 Satellite Imagery

Remotely sensed data is a sort of data that is the most compatible, affordable, and a brisk or quick course of action to provide a distinctive outlook on divulging the spatial and temporal dynamics of the change procedure in urban augmentation. In the research, satellite images have been used to acquire the desired outcomes.

The Landsat 7 ETM+ and Landsat 8 OLI satellites of the *National Aeronautics and Space Administration* (NASA) have been used to download data for the years 2002 and 2013, respectively. For 2023, Sentinel-2B data has been used. Sentinel satellites belong to the *European Space Agency* (ESA). Previous studies prove the efficacy of Landsat satellite images with spatial resolution up to 30 m and Sentinel satellite images with spatial resolution 30 m, 20 m, and 10 m.

A pair of Landsat images for both the years – 2002 and 2013 and another pair of images from Sentinel for 2023 were obtained from the *U.S. Geological Survey* (USGS) Earth Explorer website and Sentinel Data Hub, Copernicus EU website respectively. These images were used to observe land cover change tendencies during the given time frames.

Sentinel satellite images were taken for the latter year because of higher spatial resolution of up to 10 m. For each year, multiple tiles were taken since the region of interest happened to be on two different tiles. Therefore, for all three time periods, a total of six satellite images needed to be downloaded for proper coverage of the entire region of interest.

**Figure 3.1** Sentinel-2B Satellite Image over the region of interest – Both images are in TIFF format (Source: https://scihub.copernicus.eu)

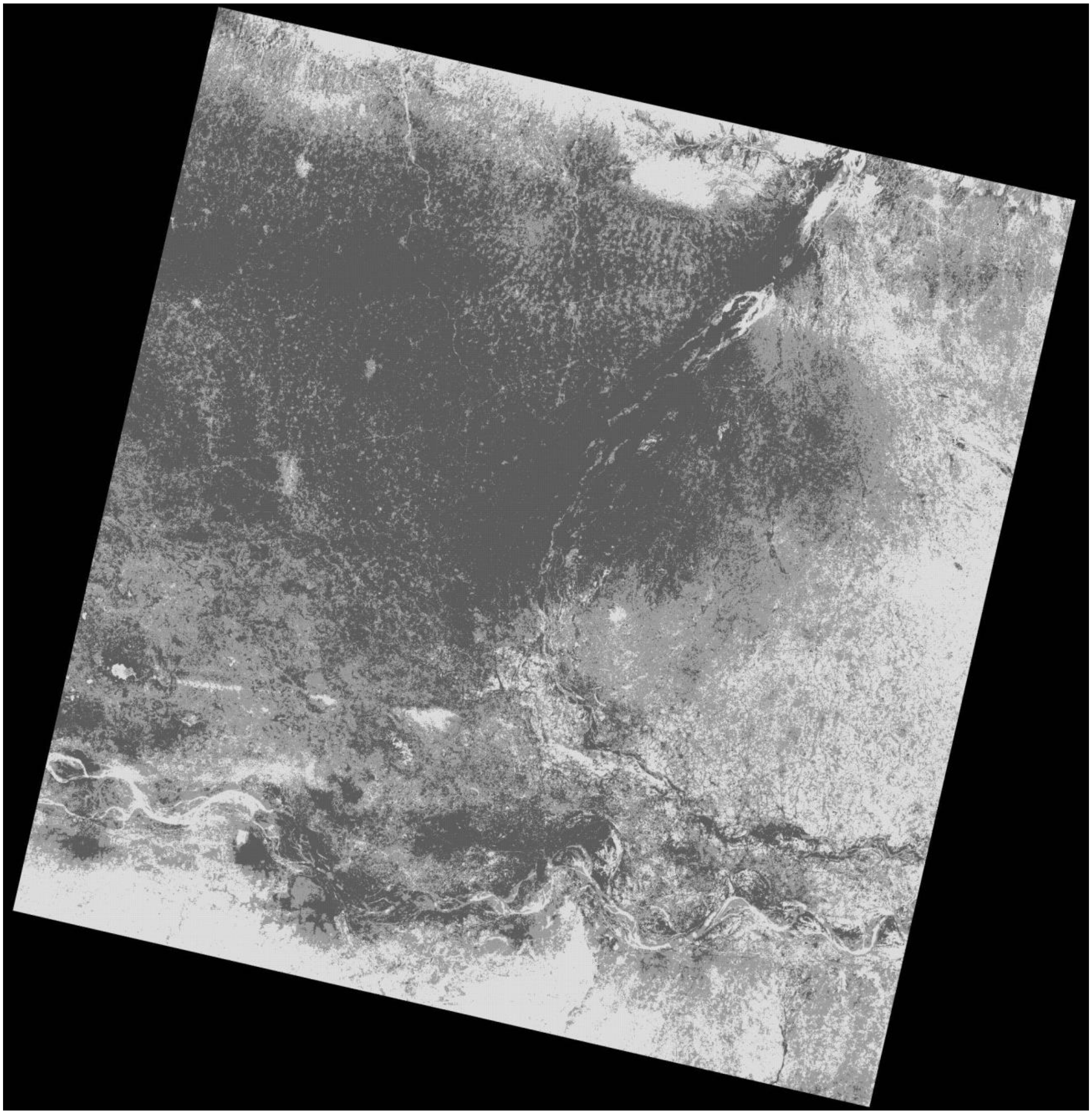

**Figure 3.2** Landsat 8 Aerosol band tile of the study area (Source: USGS Earth Explorer)

The aerosol band is unique to Landsat 8 and is used primarily to track fine particles like dust and smoke, and to peer into shallow water. This is a greyscale image of aerosol band. We can apply a color table to highlight features more profoundly [27].

**Table 3.1.** Satellite Image data set

| Year | Date | Path/Row | Satellite/Sensor | Spatial Resolution |
|---|---|---|---|---|
| 2002 | 20-10-2002 | 140/042 | Landsat-7 ETM+ | 30 m |
| | 27-10-2002 | 141/042 | | |
| 2013 | 26-03-2013 | 141/042 | Landsat-8 OLI | 30 m |
| | 10-04-2013 | 140/043 | | |
| 2023 | 12-04-2023 | | Sentinel-2B | 20 m |
| | 12-04-2023 | | | |

Throughout the previous few decades, remotely sensed data has been used in a plethora of urban expansion studies [28] because it is capable of delivering constant and persistent imagery. In addition, previous research has exhibited that remote sensing is quite effectual in studying the urban spread order.

For the stratification of remotely sensed data, GIS techniques have been integrated. For the conversion of multiple-source data into a simpler layout and to put them in unassociated layers for additional spatial analysis, GIS has been used substantially.

## 3.2 METHODOLOGY

### 3.2.1 Data Acquisition and Preprocessing

This study relied a lot on open-access data. The satellite imagery is retrieved from the *USGS Earth Explorer* website which is in collaboration with the 'National Aeronautics and Space Administration's (NASA)'. The Landsat-7 ETM+ and Landsat-8 OLI satellite images have been downloaded for the years 2002 and 2013, respectively. For the year 2023, the image from European Space Agency's (ESA) satellite Sentinel-2B was obtained. Sentinel 2B is a multispectral, high-resolution, wide-swath and twin-satellite system that orbits the earth in a sun-synchronous polar orbit. Sentinel 2A and Sentinel 2B, both the satellites collect data globally, apart from the poles, the seas, and the oceans.

To prepare the satellite image for representation and analysis, preprocessing of the data is required. This involves the correction of geometric and radiometric errors in the data. Fortunately, the Sentinel image obtained was already geometrically and atmospherically corrected.

The information about the downloaded data sets has already been represented earlier in Table 3.1. A thorough workflow chart has been shown here.

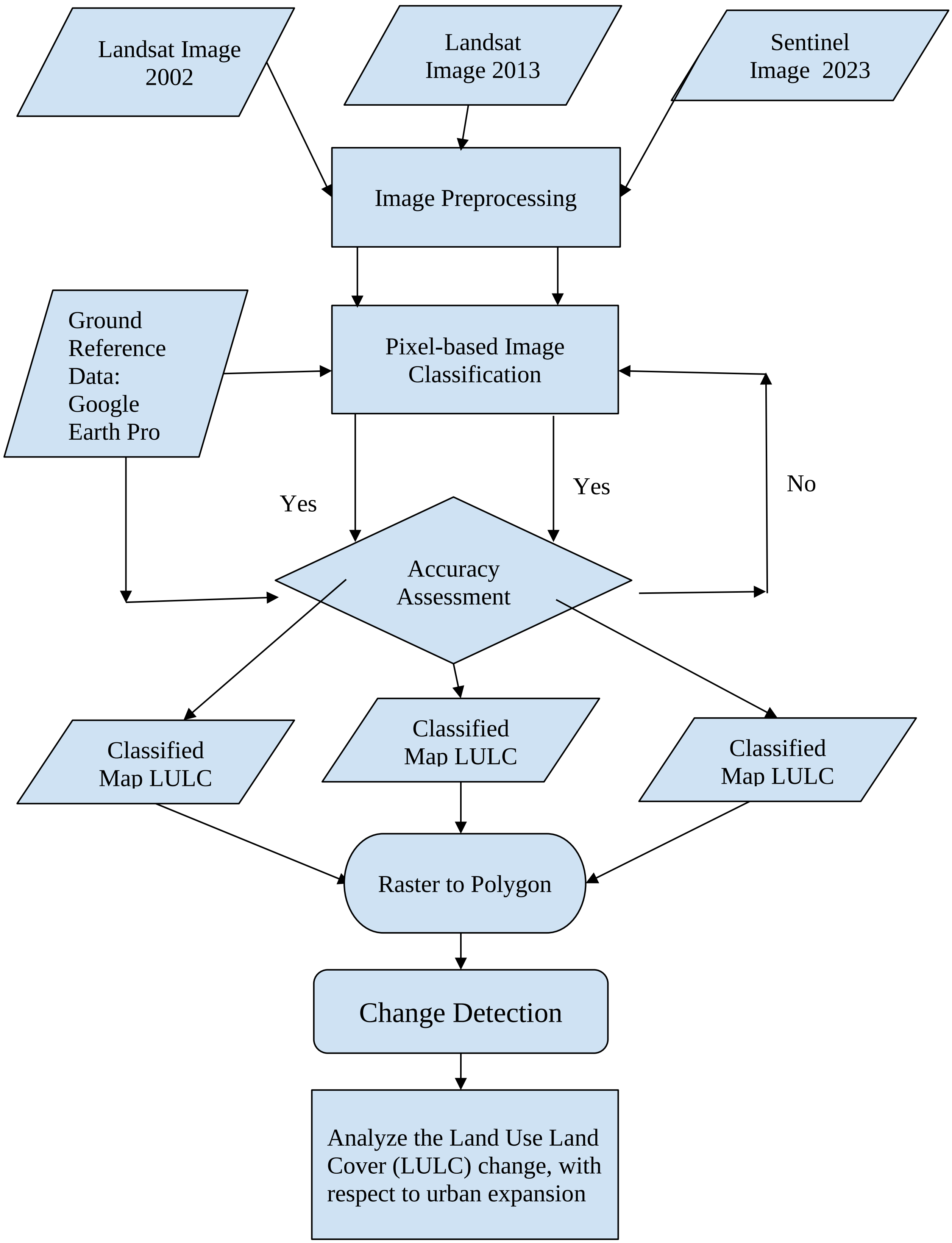


**Figure 3.3** The Methodology Flowchart

### 3.2.2 Mosaicking of Satellite Images

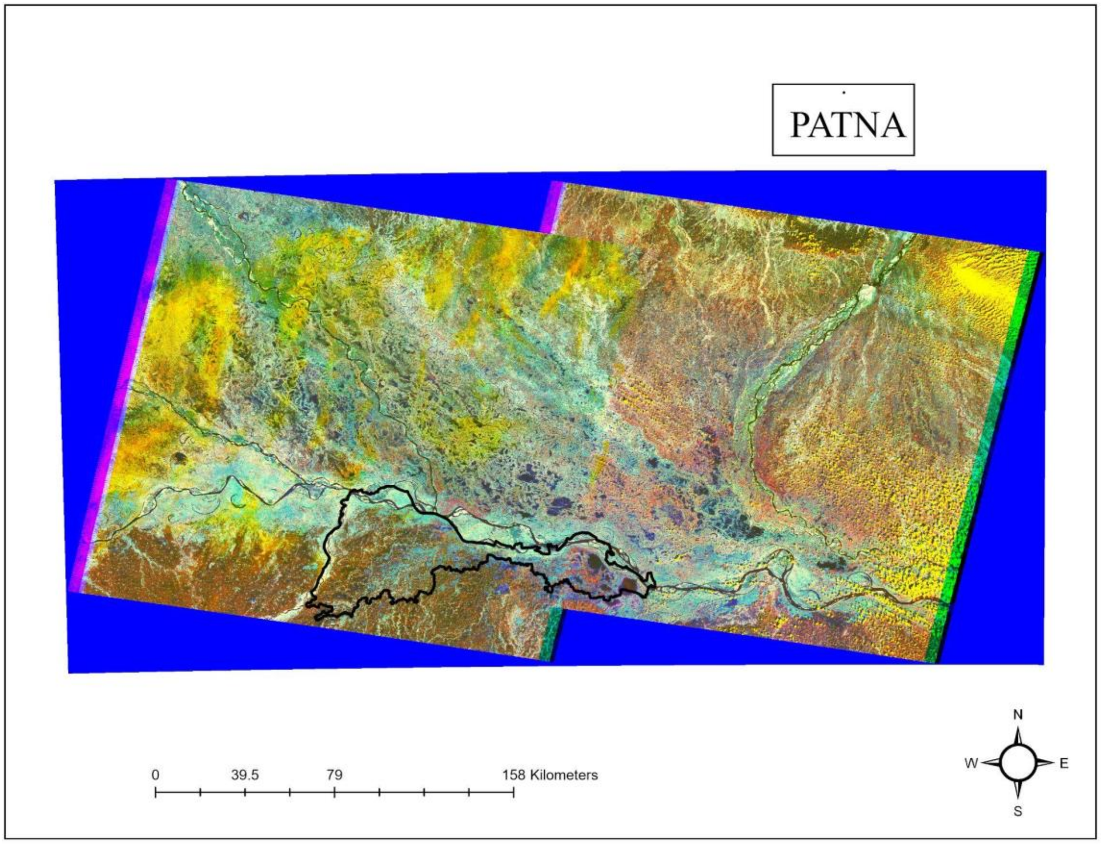


**Figure 3.4** A mosaic created from two different 2002 satellite images.

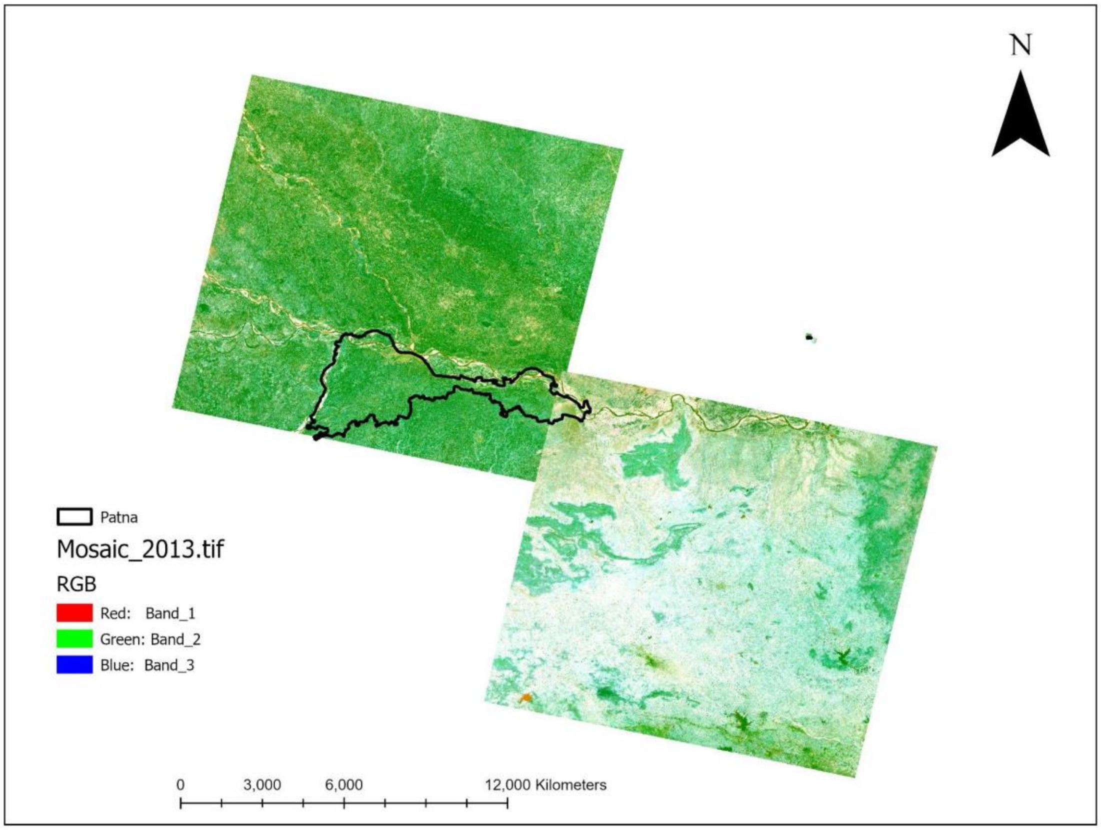


**Figure 3.5** A mosaic created from two different 2013 satellite images.

### 3.2.3 Composite Band

This study includes various important steps that are necessary to obtain the desired outcome. We took the multiple band images and combined them with an *RGB* (Red, Green, Blue) group, making their composite bands.

The composite band function allows us to combine raster datasets to form a multiband image. In this process, we imported all the bands that were required for geoprocessing and created a multiband image. In this study, we created RGB composite bands. There are various types of composite bands. For example:

- True or Natural Color Composites (NCC)
- False Color Composites (FCC)

In this study, we used False Color Composite (FCC) for the year 2002 and Natural Color Composite (NCC) for the years 2013 and 2023, respectively.

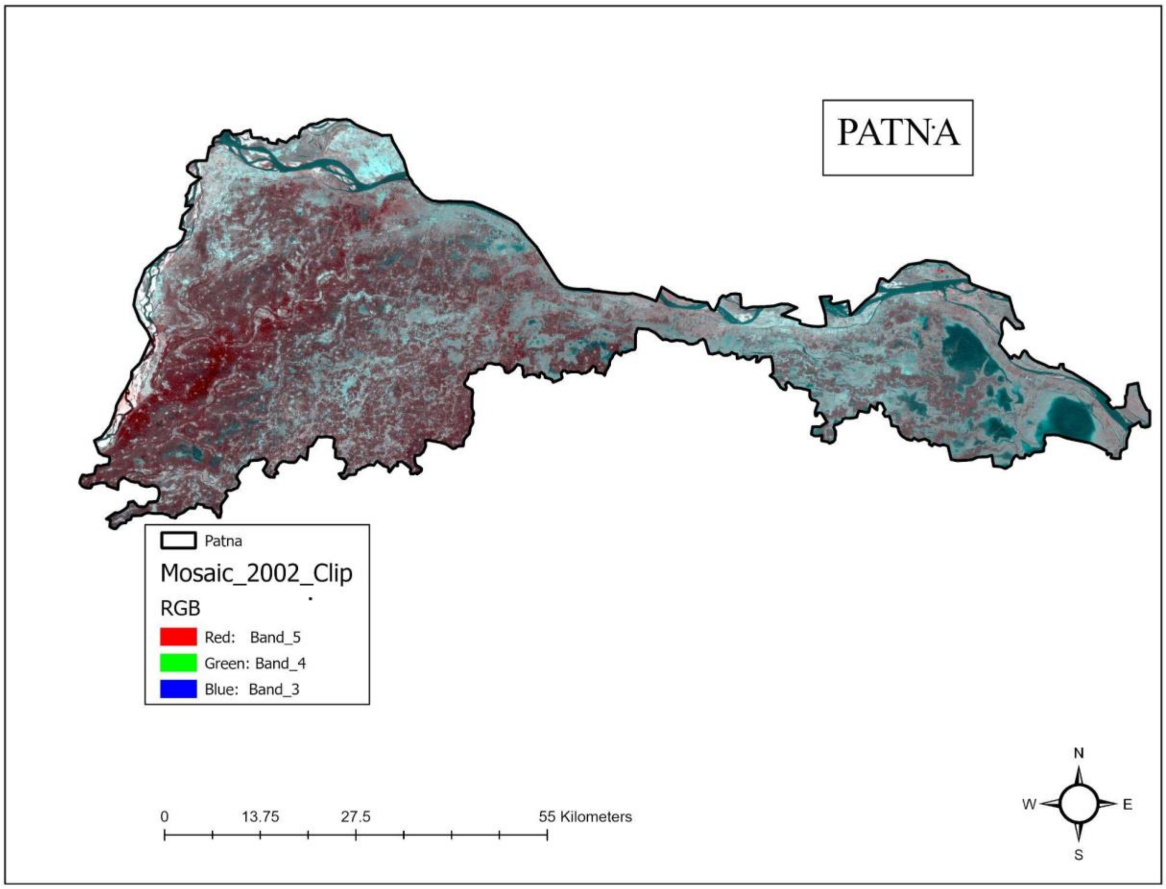


**Figure 3.6** RGB (False Color Composite) Image of study area from 2002

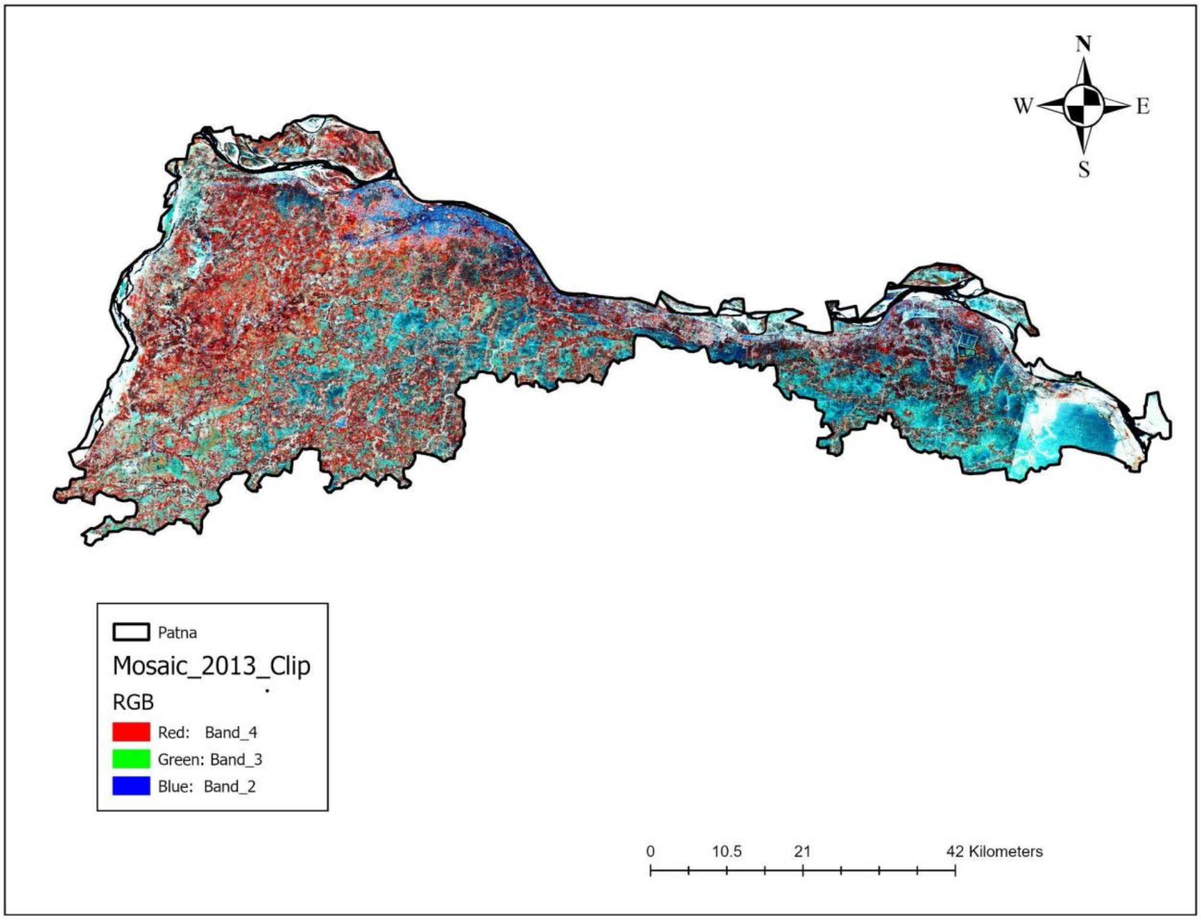


**Figure 3.7** RGB (Natural Color Composite) Image of 2013.

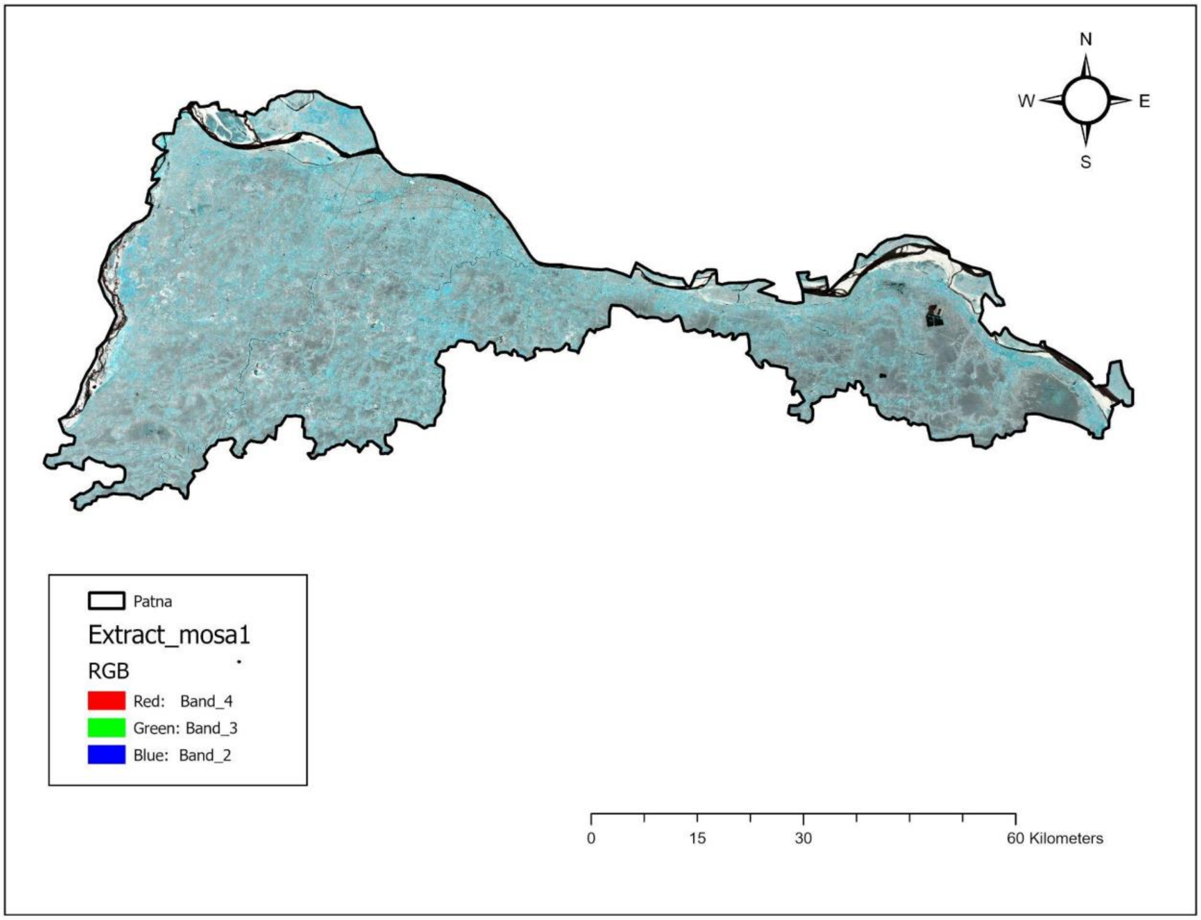


**Figure 3.8** RGB Image (Natural Color Composite) from the year 2023

### 3.2.4 Image Classification

Landsat images of the years 2002 and 2013 were obtained from the USGS, and the Sentinel satellite image of 2023 was obtained from Copernicus EU. Due to the presence of multiple tiles covering the entire area, the multiple images of different years had to be mosaiced together. All bands were included. After acquiring images, all the images were pre-processed. Once image processing gets completed, classification of image commences.

Classification is a supervised learning phenomenon that uses an ensemble of select classes (articles to recognize in images) to define and construct a template or a model to identify them incorporating marked images. Unsupervised and supervised are the two types of image classifications.

In this study, both unsupervised and supervised classifications are conducted. After the classification, the images were tested for accuracy.

The accuracy of information procured through remotely sensed data is primarily determined by accuracy assessment. These evaluations can either be qualitative or quantitative. A qualitative assessment is typically a quick comparison to see if the remotely sensed data or map is satisfactory and corresponds to what's there on the ground. Quantitative evaluation seeks to identify and quantify mistakes or errors. In these assessments, we compare map data with ground reference or ground truth data. Accuracy assessment is important because remotely sensed data is often used for mapping and developing models for management and decision-making purposes [29].

In supervised image classification, there are mainly two types of classifications that are widely used:

- Pixel-based classification
- Object-oriented classification

Pixel-based procedures are the main means of image processing. Conventional supervised and unsupervised stratification are both established on a single pixel. The goal of a classical image classification process is to spontaneously categorize all pixels of the image into land cover classes or themes. Generally, multispectral data is utilized to perform the classification.

The filtering of the image into meaningful items is the first step in object-oriented classification. The segmentation algorithm is a region-merging technique from the bottom-up. It commences by treating each pixel as a separate entity. Subsequently, adjacent pairs of image objects are merged to create bigger segments. The next step is classification after image segmentation. The classification description in an object-oriented classification approach is knowledge-based. The objects then become assigned according to their meeting certain properties. There is a fuzzy logic to this type of classification.

**Table 3.2** Attributes used for classification in different methods.

| | Color/Spectral | Shape | Area | Texture | Content |
|---|---|---|---|---|---|
| Pixel-based | ✓ | ✓ | ✕ | ✓ | ✕ |
| Object-oriented | ✓ | ✓ | ✓ | ✓ | ✓ |

### 3.2.5 Pixel based Classification

We had employed pixel based categorization or classification for assigning the categories in the images. Supervised classification analytics have been administered in pixel based classification.

Paradigmatic pixel based classification automatically categorizes all pixels in an image into land cover classes or themes in a pixel-by-pixel fashion. The data of each pixel is applied as the quantitative basis for categorization [30].

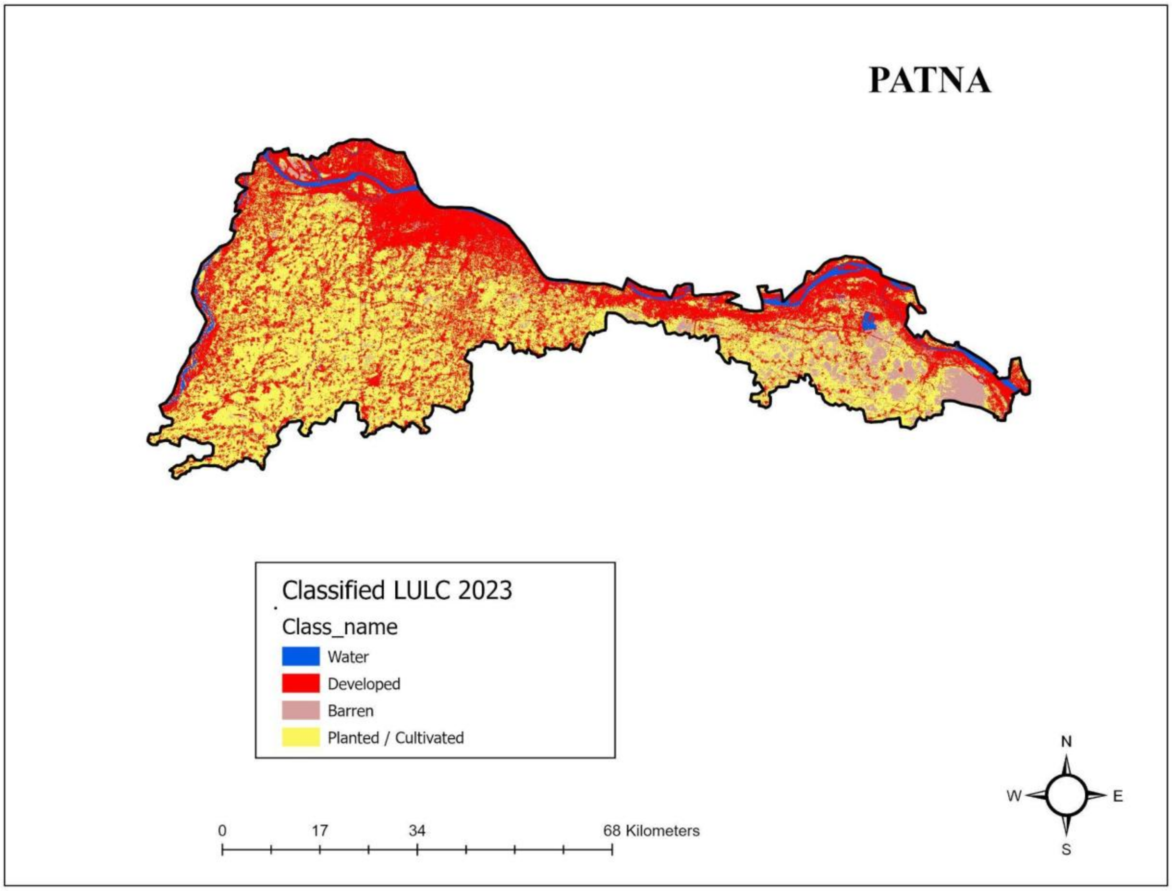


**Figure 3.9** A pixel based classified LULC image of 2023

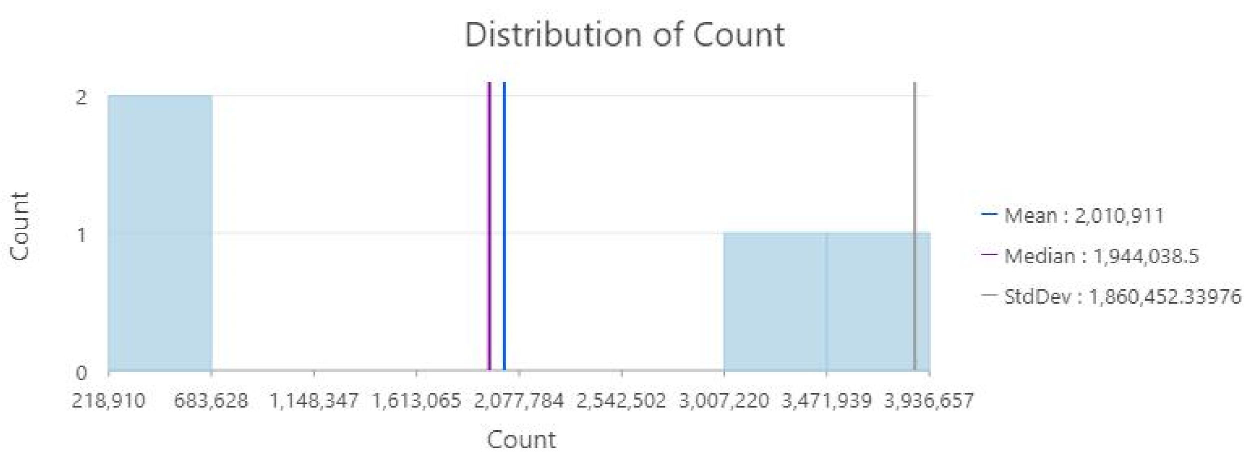


**Figure 3.10** Count Distribution of LULC map of 2023

### 3.2.6 Accuracy Assessment

Any categorization or classification effort must include an accuracy assessment. It compares the categorized or classified image to another data source that is reliable and accurate or simply ground truth. Ground truth is gathered in the field, but to be honest, it is quite a bit expensive and time-consuming. High-resolution image interpretation can be used as a source for providing ground truth data. GIS data layers, or existing classified imagery are sources for ground truth data as well. To evaluate and quantify the accuracy of a classified image, it must be compared to a reference data set whose validity is presumed to be true [31]. The process has been used to estimate the accuracy of classified images. A full accuracy assessment includes a report on User accuracy and Producer accuracy.

The most typical method for determining the correctness of a classified map is to generate a random set of points/locations inside the classified image of the area of interest and then compare them with the previously available ground truth data in a confusion matrix.

- **Accuracy Assessment formula**

User's Accuracy $= \dfrac{Number\ of\ correctly\ classified\ pixels\ in\ each\ category}{Total\ number\ of\ classified\ pixels\ in\ that\ category}$ x 100

Producer's Accuracy = $\dfrac{Number\ of\ correct\ classified\ pixels\ in\ each\ category}{total\ number\ of\ reference\ pixels\ in\ that\ category}$ x 100

Overall Accuracy = $\dfrac{Total\ number\ of\ correctly\ classified\ pixels}{Total\ number\ of\ reference\ pixels}$ x 100

*Kappa coefficient (T)* = $\dfrac{(TS\ x\ TCS) - \sum(Column\ Total\ x\ Row\ Total)}{(TS)2 - \sum(Column\ Total - Total\ Row)}$ x 100

### 3.2.7 Conversion of Raster Dataset to Polygon Dataset

Vector data is a spatial data that is illustrated as points, lines, or polygons. Whereas raster data is an illustration of geographic data in the form of a 'matrix of cells', each bearing an attribute value. To convert a raster to a point feature class, we use the 'Raster to Polygon tool' from the toolbox in *ArcGIS Pro 3.1*.

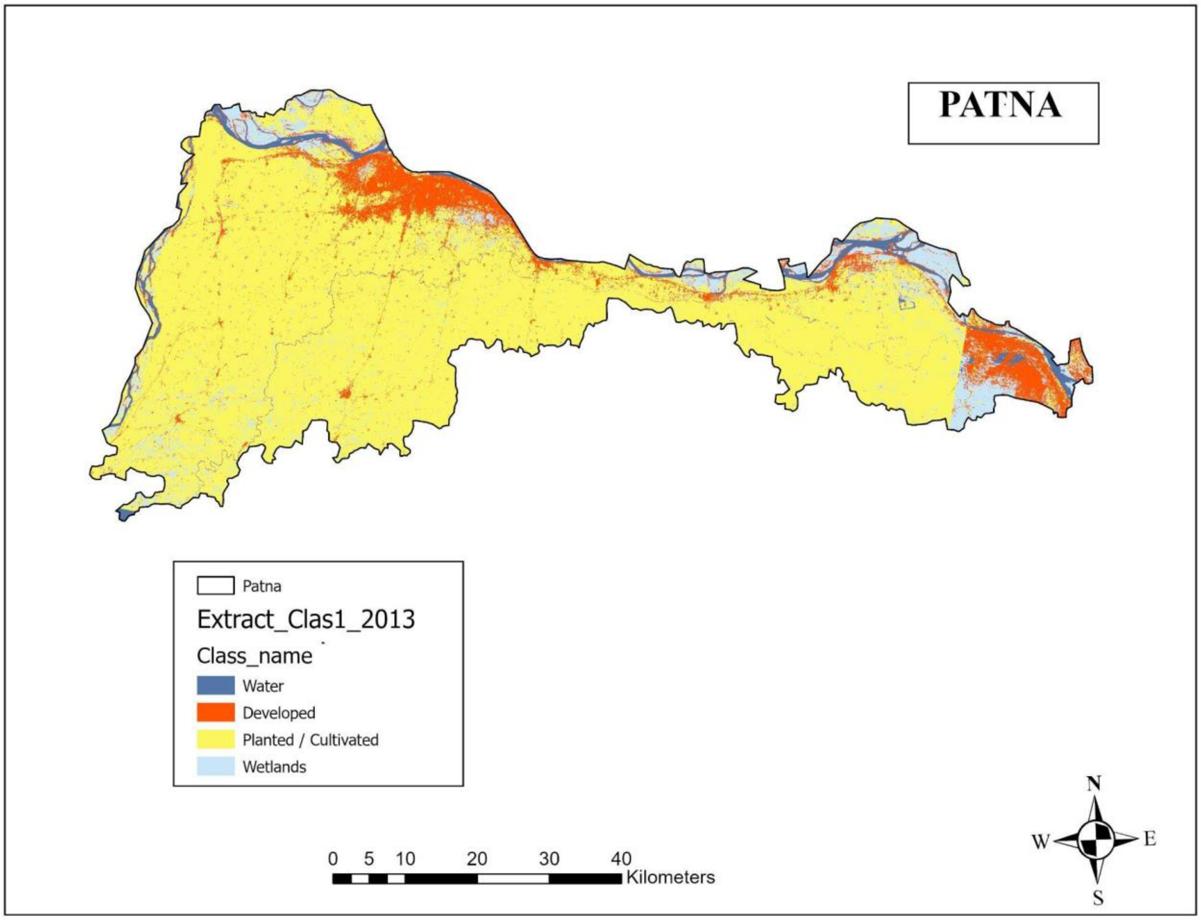


**Figure 3.11** A Raster LULC Image

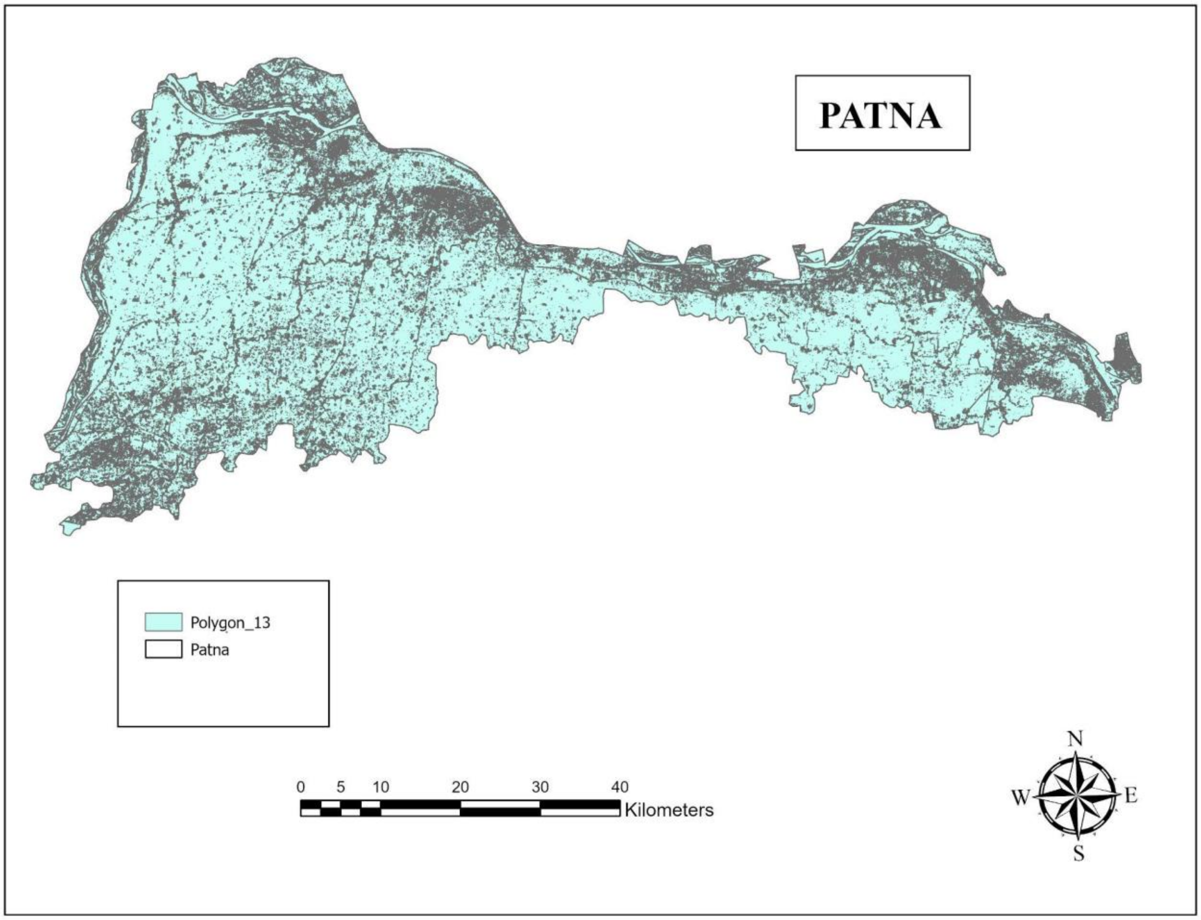


**Figure 3.12** A Raster to Polygon converted image

### 3.2.8 Change Detection

Change detection in remote sensing is an essential aspect of remote sensing image interpretation that compares and examines two (or more) remotely sensed images collected of the similar location at different time-frames. Change detection can be defined as the process of recognizing dissimilarities in the condition of an object or phenomenon by distinguishing it at distinctive times [32].

Change detection is performed to analyze and visualize changes in land cover in the region of interest. Change detection is done to conclude which land use class is transforming to another. Land change detection procedures involve image overlay, comparison of classification of land cover, image intersect, change vector analysis, etc. [33].

All three classified images were taken, and an 'intersect' tool was used over them to detect the change. The 'Intersect tool' detects the geometric intersection of an unlimited number of feature classes and feature layers. 'Intersect' generates a new feature by combining the similar regions or edges of any two (or more) specified features of the same geometry type [34].

### 3.4 SOFTWARES

Various software programs necessary to perform the operations of the research were:

5) *ArcGIS Pro 3.1*

- For Satellite Image Processing
- For Accuracy assessment
- For Change detection

*ii) Google Earth Pro*

- For Ground truth data
- For Accuracy assessment

*iii) MATLAB R2023a*

- For implementation of Change detection

*iv) Google Sheets*

- For plotting graphs

## 4.1 IMAGE CLASSIFICATION – LULC

LULC classification is the procedure of allocating and categorizing land cover classes to pixels [35]. In this research, we executed the pixel based classification method. This ensures the classification of each pixel into a particular feature or class. We identified four different types of features in the study area. They were:

I) Water Bodies

II) Developed or Built-Up Area

III) Plantation or Cultivation

IV) Wetlands

Based on these classes or features, we classified the images of the years 2002, 2013, and 2023. The classified images are exhibited in Figures 4.1, 4.2, and 4.3.

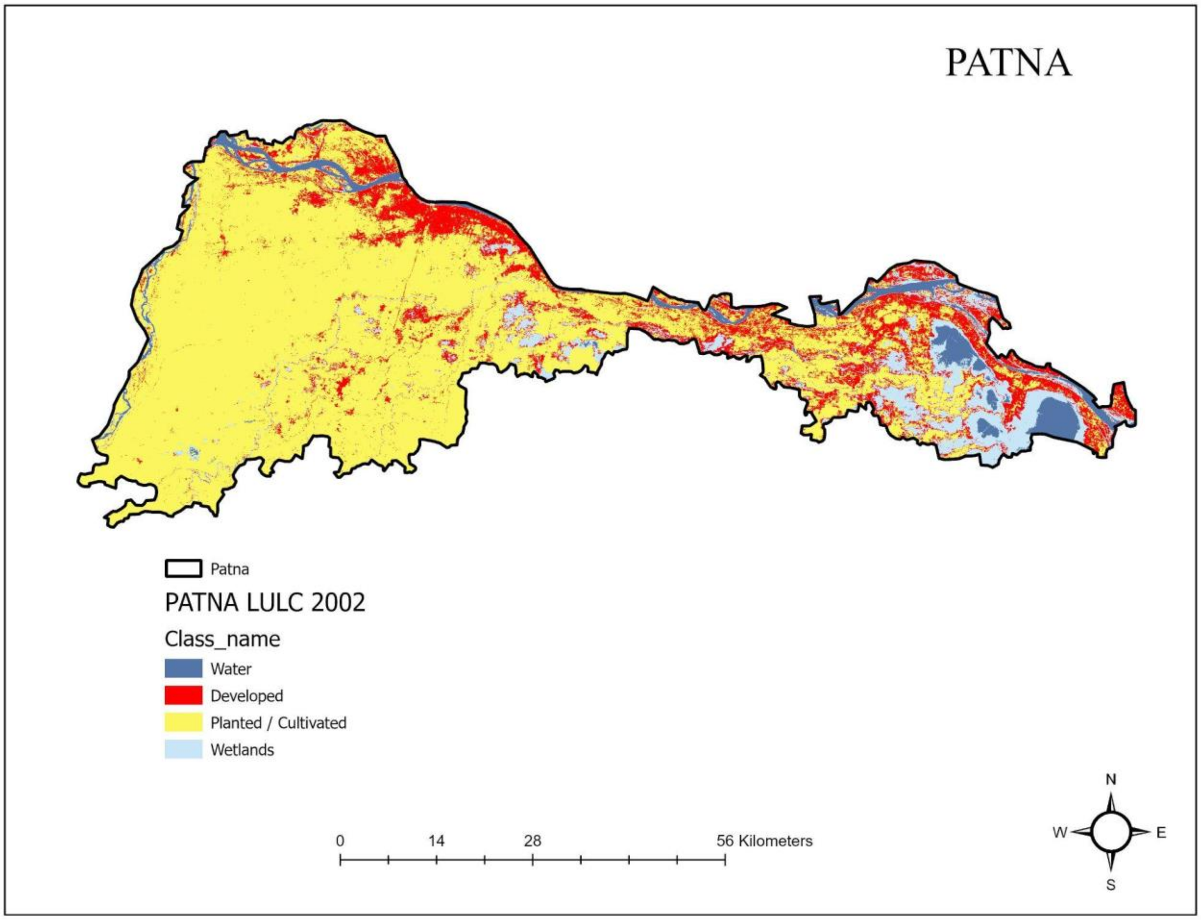


**Figure 4.1** Classified Image of 2002 – Land Use Land Cover (LULC) Map

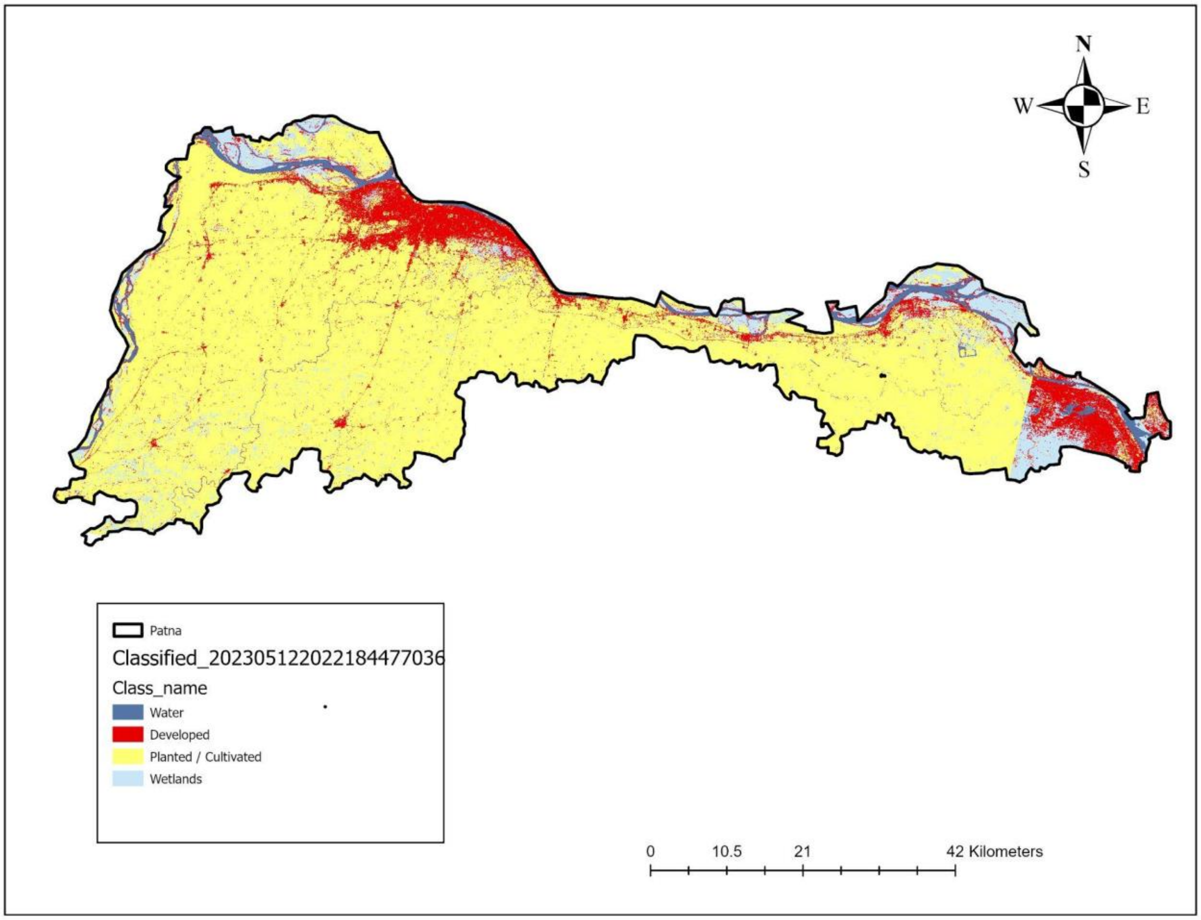


**Figure 4.2** Classified Image of 2013 – Land Use Land Cover (LULC) Map

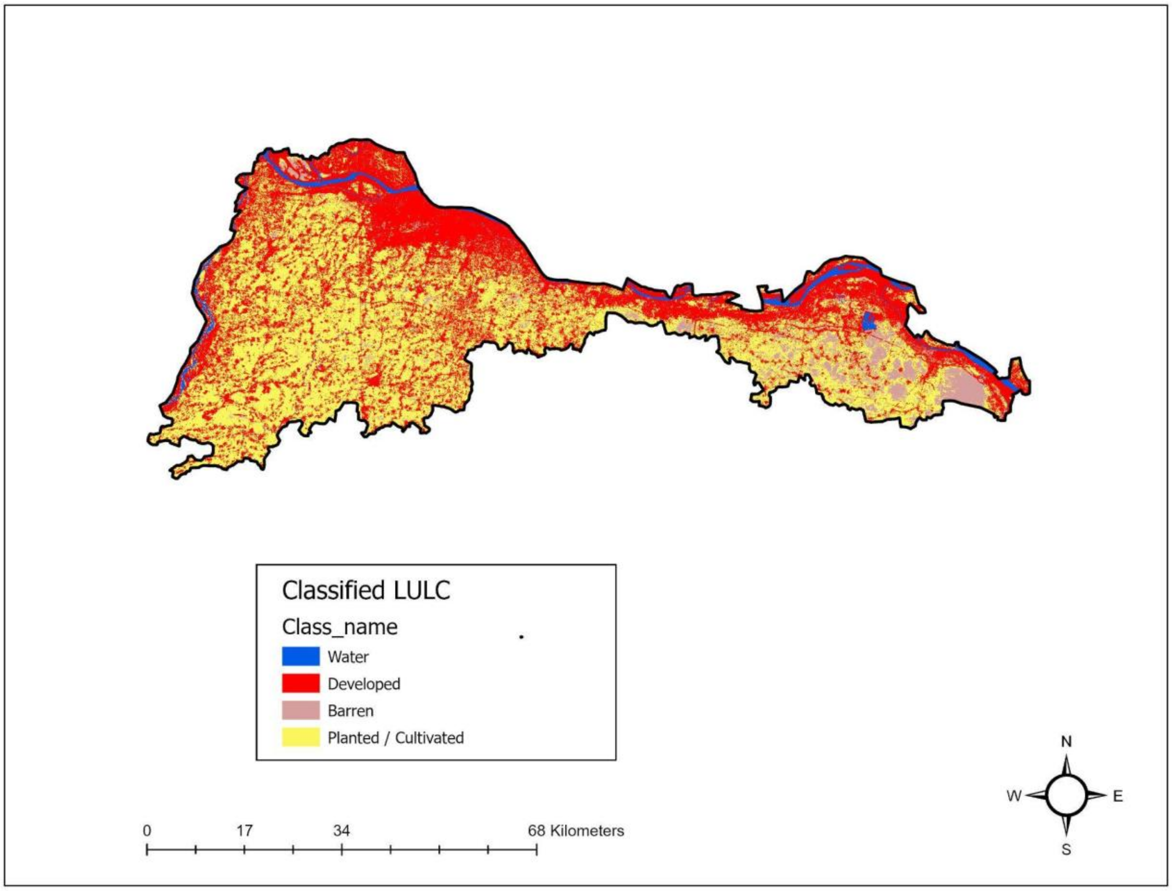


**Figure 4.3** 2023 Classified image – LULC map

## 4.2 ACCURACY ASSESSMENT

The accuracy assessment juxtaposes the categorized image to another data source deemed accurate or ground truth data. High resolution imagery, existing classified imagery or GIS data layers may be utilized to engender ground truth data.

Thus, as a result accuracy evaluation employs a reference dataset to determine the classification accuracy of the image.

To evaluate the validity of a classified map, we created a collection of random locations on the classified image and compared them to ground truth data. In this study, we used *Google Earth Pro* as a reference dataset and then compared them in a confusion matrix.

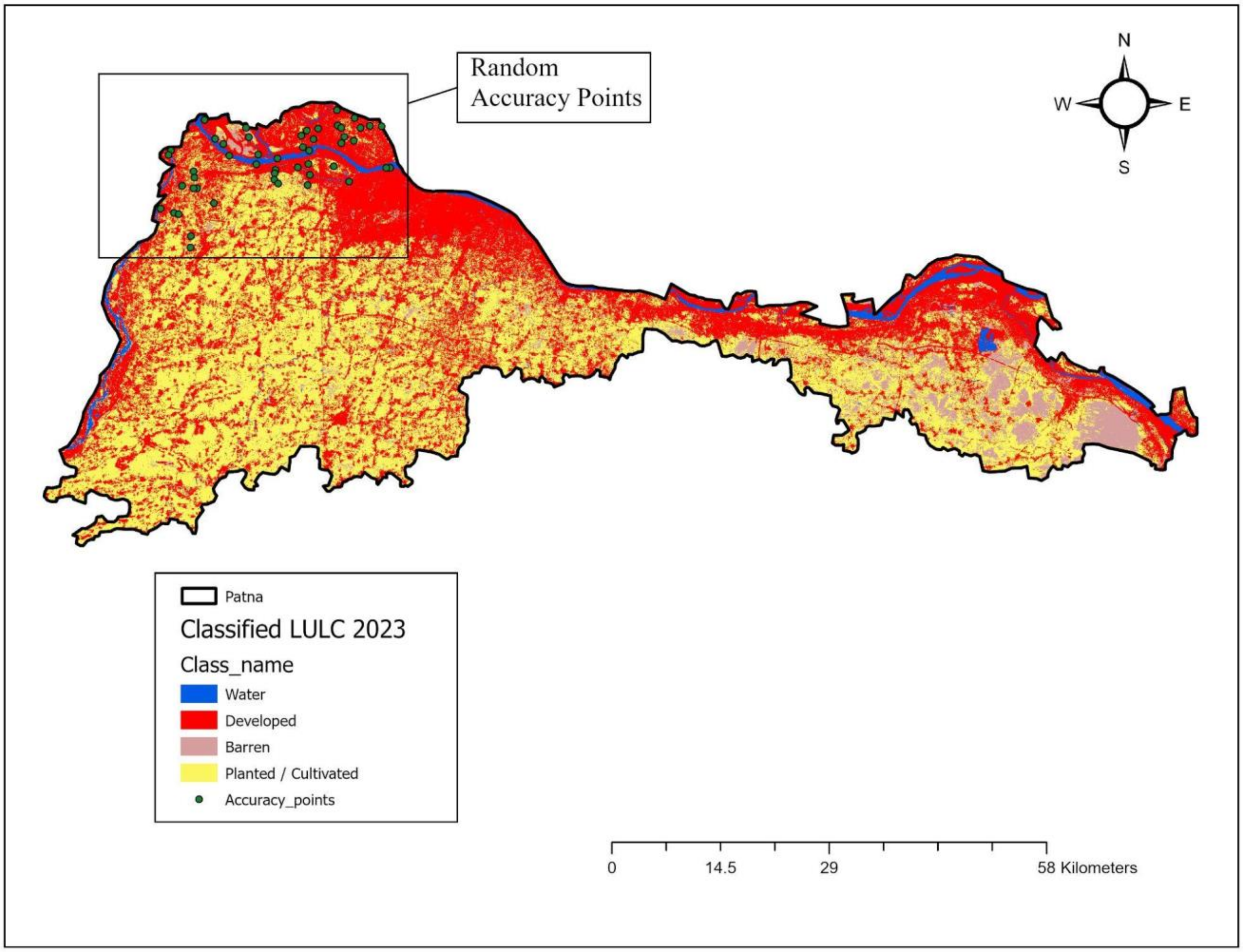


**Figure 4.4** Random Accuracy Points for comparison with Ground Truth Data and accuracy assessment

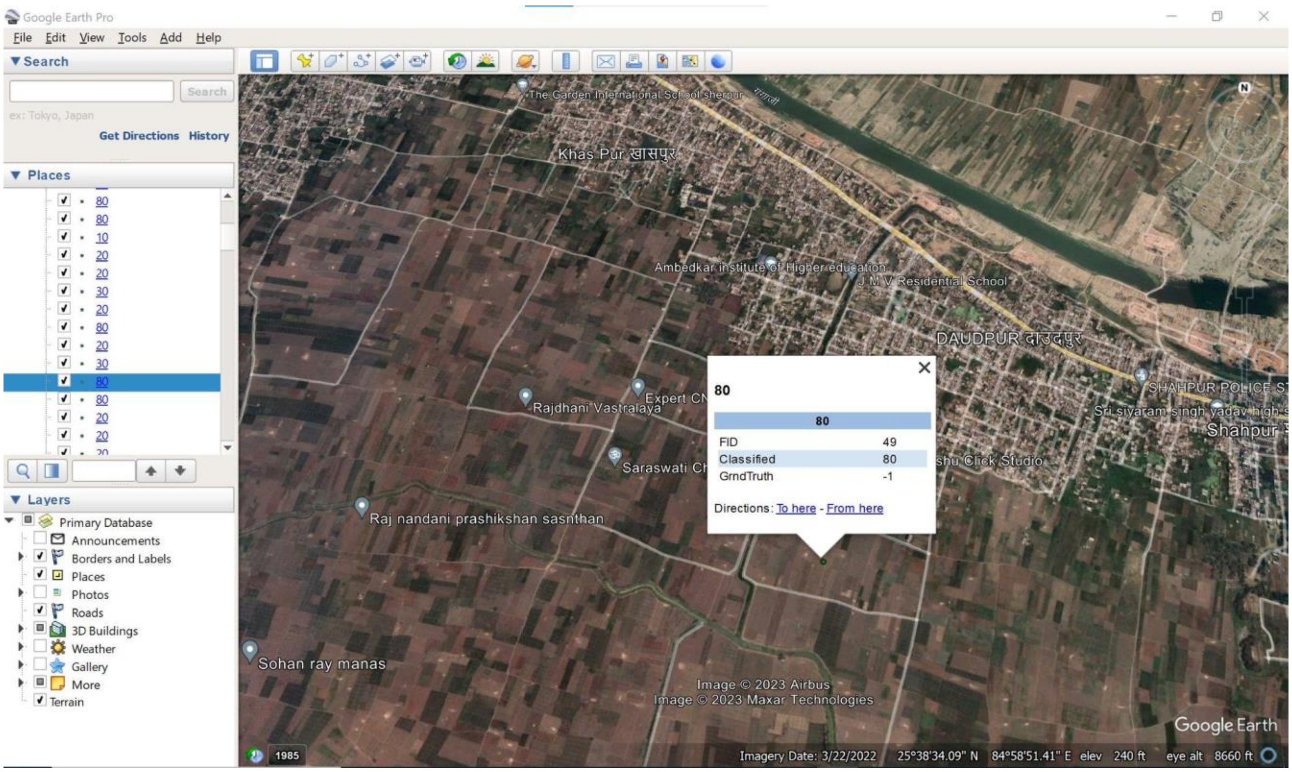


**Figure 4.5** Comparing Random Accuracy Points to Ground Truth Data on *Google Earth Pro*

### 4.2.1 Confusion Matrix

Table 4.1 depicts the classification's confusion matrix. It indicates the classification accuracy of LULC maps and indicates the overall accuracy.

**Table 4.1** Confusion Matrix Table

| OBJECTID * | Class Value | C_10 | C_20 | C_30 | C_80 | Total | User Accuracy | Kappa |
|---|---|---|---|---|---|---|---|---|
| 1 | C_10 | 6 | 0 | 0 | 0 | 6 | 1 | 0 |
| 2 | C_20 | 1 | 12 | 6 | 9 | 28 | 0.421429 | 0 |
| 3 | C_30 | 0 | 1 | 3 | 0 | 4 | 0.55 | 0 |
| 4 | C_80 | 0 | 0 | 1 | 11 | 12 | 0.916667 | 0 |
| 5 | Total | 7 | 10 | 8 | 25 | 50 | 0 | 0 |
| 6 | Producer Accuracy | 0.857143 | 0.9 | 0.125 | 0.44 | 0 | 0.71 | 0 |
| 7 | Kappa | 0 | 0 | 0 | 0 | 0 | 0 | 0.577031 |

### 4.2.2 Overall Accuracy

This accuracy provides the overall findings of the confusion matrix. The given formula for calculating overall accuracy is as follows:

$$\text{Overall Accuracy} = \frac{Total\ number\ of\ correctly\ classified\ pixels}{Total\ number\ of\ referenced\ pixels} \text{ x } 100$$

$$\frac{32}{50} \text{ x } 100 = 64\ \%$$

$$\text{User's Accuracy} = \frac{Number\ of\ correctly\ classified\ pixels\ in\ each\ category}{Total\ number\ of\ classified\ pixels\ in\ that\ category} \text{ x } 100$$

$$= 71\ \%$$

$$\text{Kappa coefficient} = \frac{(TS\ x\ TCS) - \sum(Column\ Total\ x\ Row\ Total)}{(TS)2 - \sum(Column\ Total - Total\ Row)} \text{ x } 100$$

$$= 57\ \%$$

### 4.2.3 Kappa coefficient

The Kappa statistic is used to determine the compatibility or agreement between two dataset categories. It is also used to evaluate or gauge the accuracy of predictive models by estimating the acceptance linking the model and a collection of surveyed sample points [36].

In this study, 50 accuracy points per image or Ground Control Points (GCP) were taken to evaluate the classification of images from 2002, 2013, and 2023, respectively, using *Google Earth Pro.*

The accuracy assessment has been done for all three timelines separately. The overall accuracy of the output was around 64% and the Kappa coefficient's output was 57%. Thus, according to the classification scale given by [37], the classification turned out to be in the 'good' range.

**Table 4.2** Kappa Coefficient compatibility or agreement (Source:

| Serial No | Kappa Coefficient | Rate |
|---|---|---|
| 1. | KC > 0.85 | Excellent |
| 2. | 0.85 > KC > 0.7 | Very Good |
| 3. | 0.7 > KC > 0.55 | Good |
| 4. | 0.5 > KC > 0.4 | Fair |
| 5. | Less than 0.4 | Poor |

## 4.3 CHANGE DETECTION ANALYSIS

Remotely sensed images have been widely used to detect changes in Land Use and Land Cover (LULC) [38].

### 4.3.1 Raster to Polygon Conversion

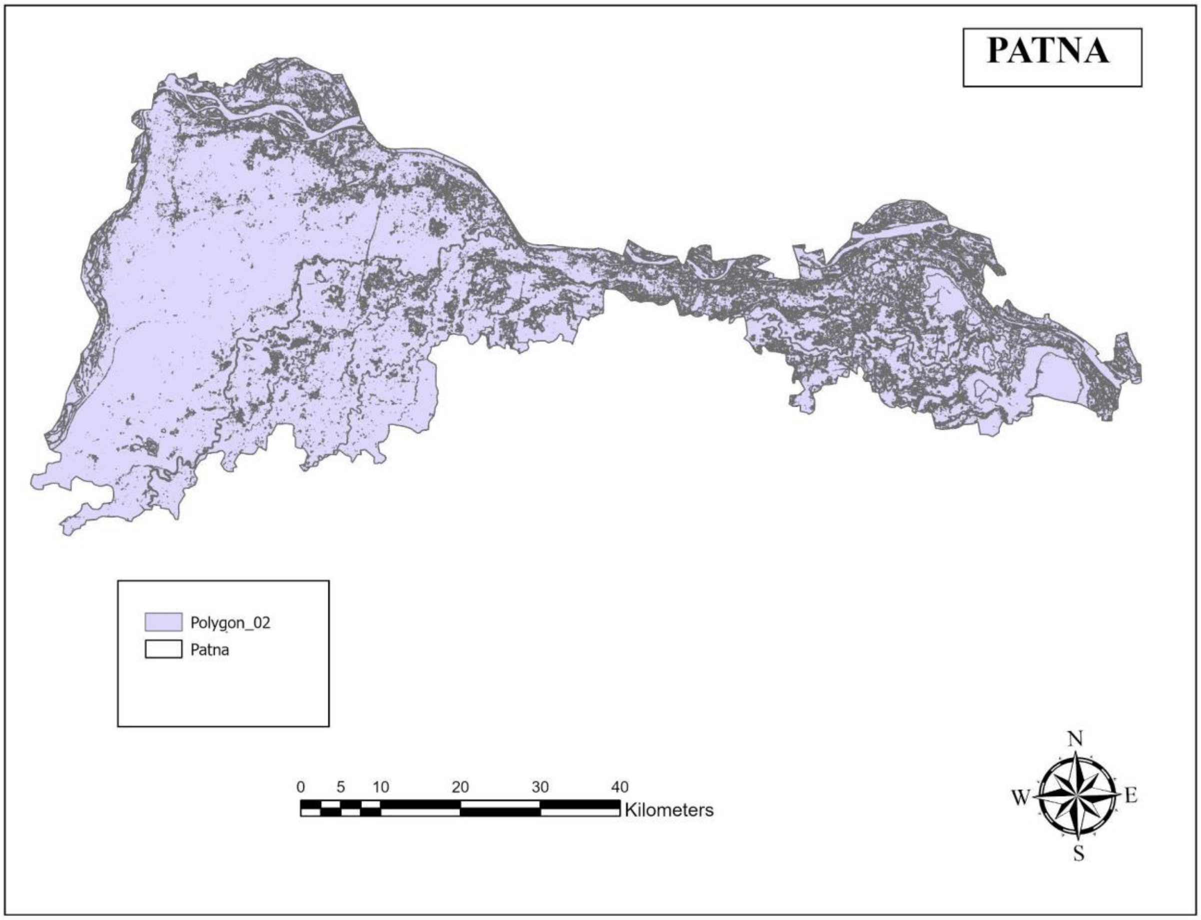


**Figure 4.6** Raster to Polygon converted image of 2002

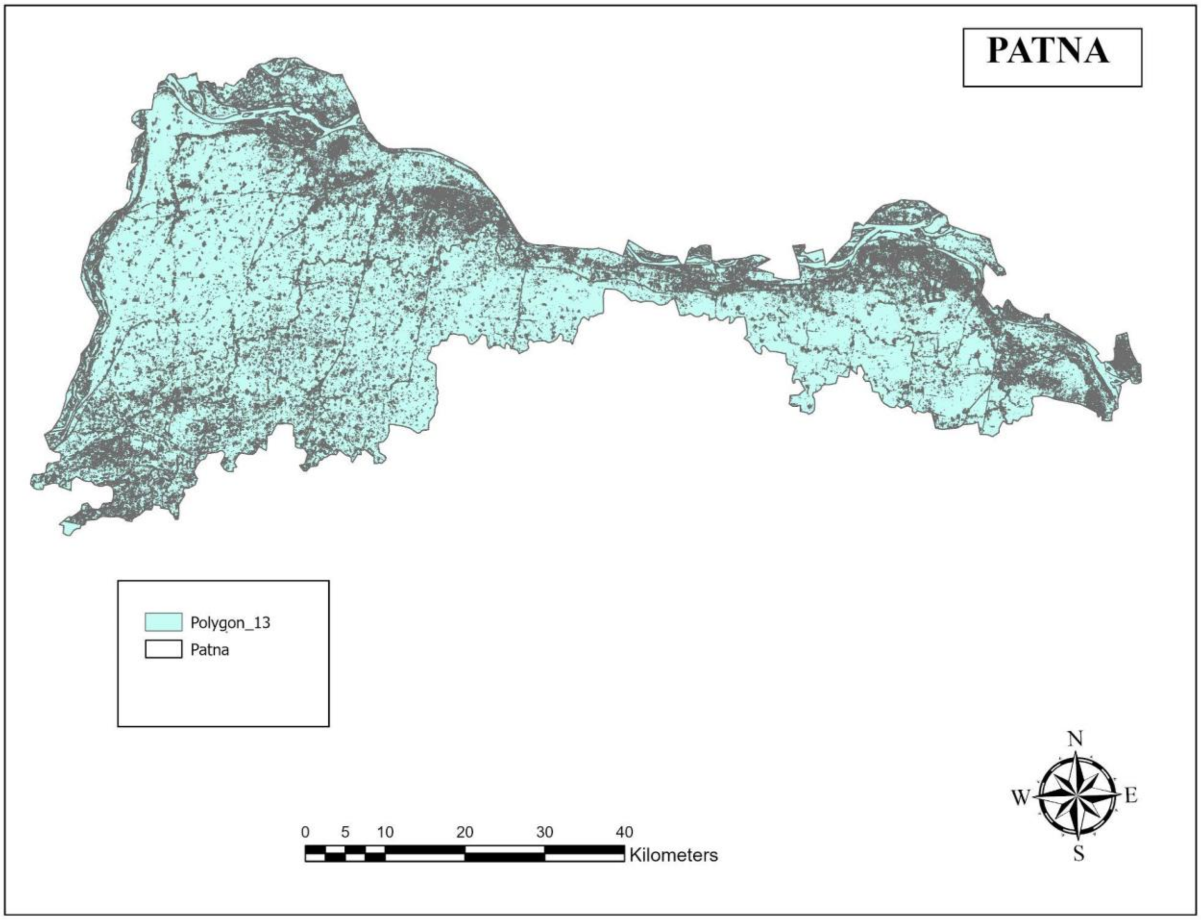


**Figure 4.7** Raster to Polygon converted image of 2013

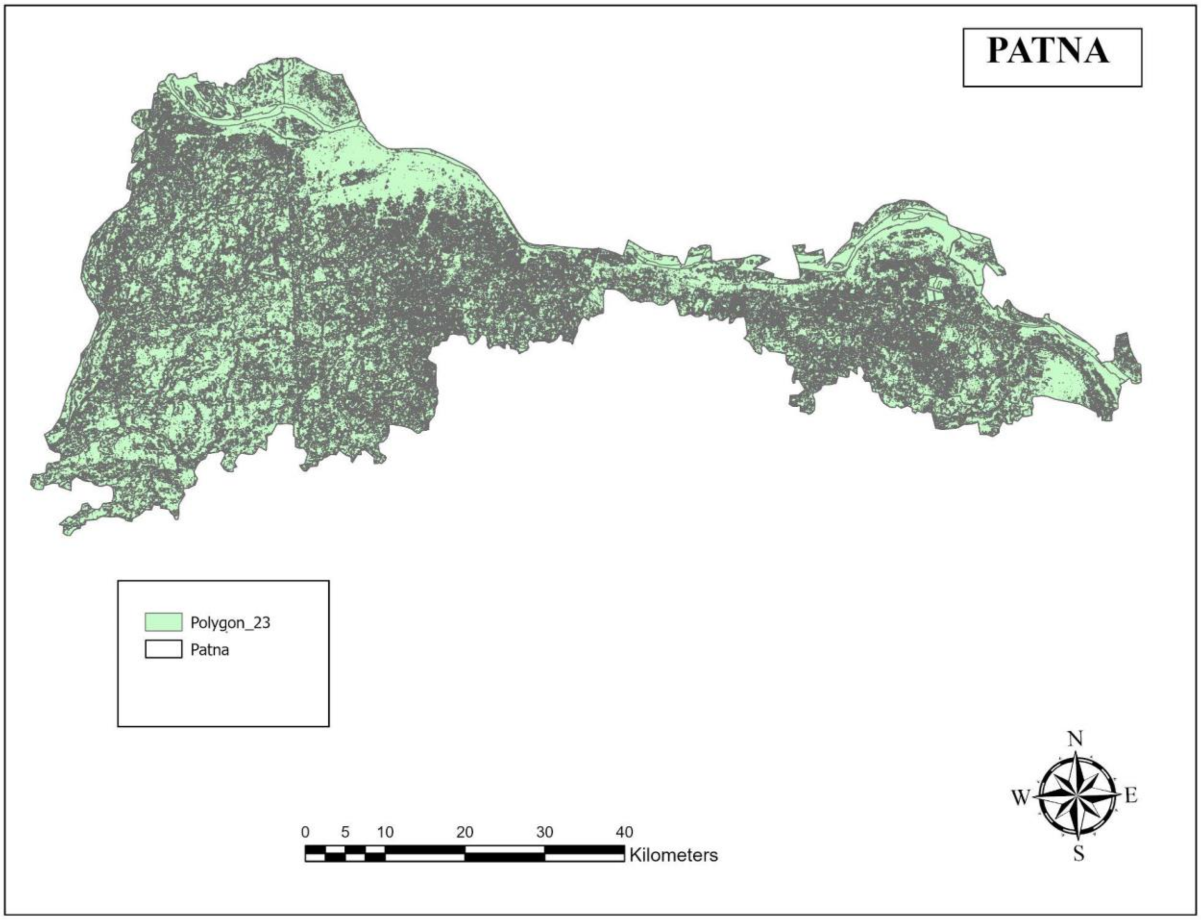


**Figure 4.8** Raster to Polygon converted image of 2023

### 4.3.2 Change in Area of all features/classes

Once the raster datasets have been converted to polygon datasets, we then use the *Intersect* tool of the ArcGIS Pro software for analyzing change detection. This tool intersects all three images from 2002, 2013, and 2023 into one raster. This allows us to compare the total change in features in all the images.

The entire data can now be seen in the image's attribute table. Through this table, we start calculating the changes in area, changes in classes, etc.

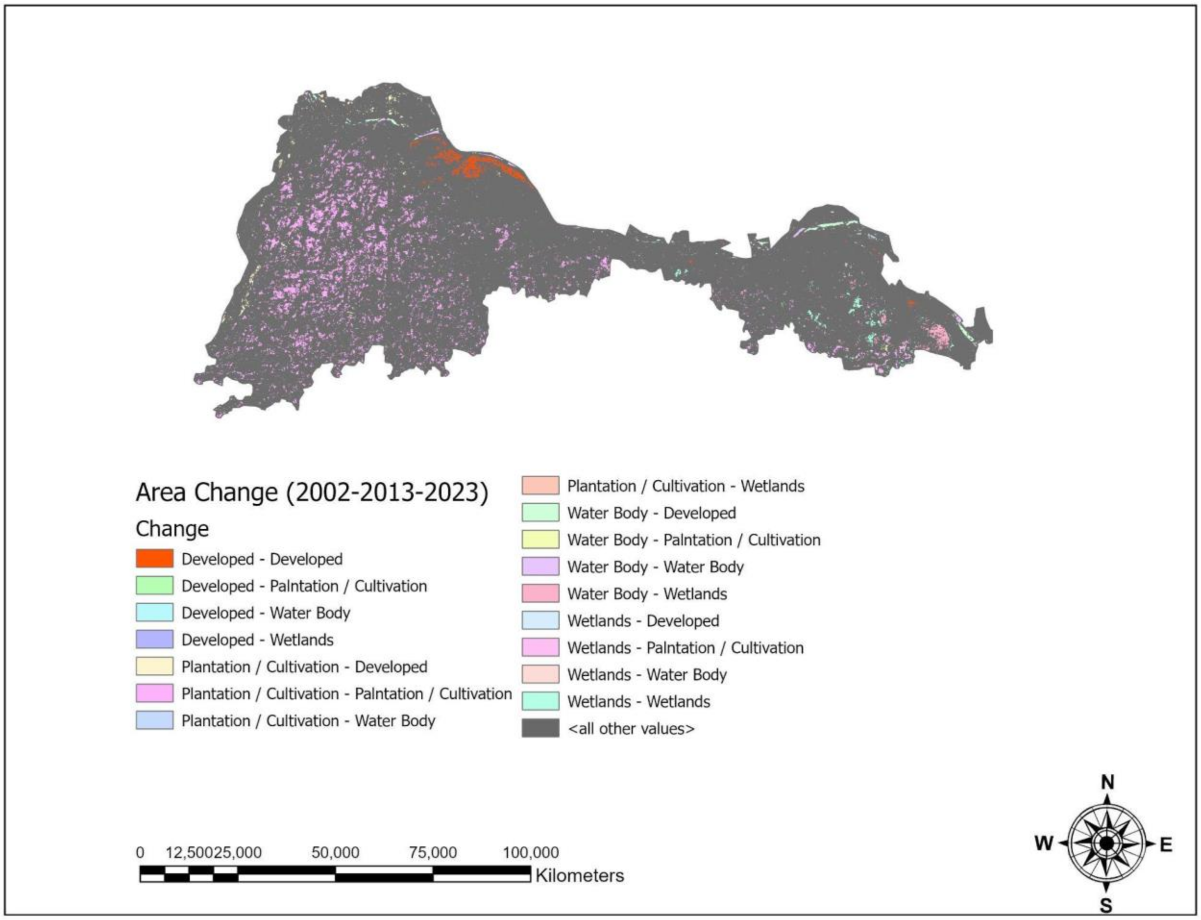


**Figure 4.9** Intersecting Image of all three LULC images. Feature wise representation of change in area

The study area's Land Use Land Cover (LULC) has undergone significant changes during the two decades. An increase of more than 109 square kilometers in the city's major metropolitan region, whereas the entire extent of developed region has reached out to a whopping 1295.03 square kilometers out of the entire 3203.719 square kilometers of area of the entire Patna district, which comprises 6 sub-districts or sub divisions.

This volcanic expansion has invaded and changed the natural land cover and transformed the land [39]. This can be demonstrated by collating the LULC maps shown earlier in Figures 4.6, 4.7, and 4.8. These changes have impacted us in both positive and negative ways. The LULC change analysis has revealed that the rampant expansion of the built-up area has resulted in a fall in vegetation cover in the city and has also affected the water bodies in the city.

Although the presence of the *Ganges* restricts the expansion of the city towards the north, this doesn't seem to hamper the rate of development in the city.

**Table 4.3** Output of change in area of all features

| FID | Change | Total Area |
|---:|---:|---:|
| 0 | Water Body – Water Body | 19.839331 |
| 1 | Water Body – Developed | 22.422407 |
| 2 | Water Body – Wetlands | 2.719746 |
| 3 | Water Body – Plantation / Cultivation | 1.727379 |
| 4 | Water Body – Water Body | 2.89304 |
| 5 | Water Body – Developed | 7.87221 |
| 6 | Water Body – Wetlands | 19.988681 |
| 7 | Water Body – Plantation / Cultivation | 1.702061 |
| 8 | Water Body – Water Body | 2.777043 |
| 9 | Water Body – Developed | 8.552858 |
| 10 | Water Body – Wetlands | 13.955453 |
| 11 | Water Body – Plantation / Cultivation | 10.557767 |
| 12 | Water Body – Water Body | 6.378325 |
| 13 | Water Body – Developed | 26.44083 |
| 14 | Water Body – Wetlands | 10.178213 |
| 15 | Water Body – Plantation / Cultivation | 6.13592 |
| 16 | Developed – Water Body | 4.39835 |
| 17 | Developed – Developed | 7.424892 |
| 18 | Developed – Wetlands | 0.43813 |
| 19 | Developed – Plantation / Cultivation | 0.79955 |
| 20 | Developed – Water Body | 2.084324 |
| 21 | Developed – Developed | 126.286913 |
| 22 | Developed – Wetlands | 3.528002 |
| 23 | Developed – Plantation / Cultivation | 9.568434 |
| 24 | Developed – Water Body | 2.893218 |

| | | |
|---|---|---|
| 25 | Developed – Developed | 94.234658 |
| 26 | Developed – Wetlands | 25.683088 |
| 27 | Developed – Plantation / Cultivation | 117.740621 |
| 28 | Developed – Water Body | 6.353104 |
| 29 | Developed – Developed | 58.064779 |
| 30 | Developed – Wetlands | 3.97164 |
| 31 | Developed – Plantation / Cultivation | 18.734209 |
| 32 | Plantation / Cultivation – Water Body | 7.664454 |
| 33 | Plantation / Cultivation – Developed | 8.663412 |
| 34 | Plantation / Cultivation – Wetlands | 0.760218 |
| 35 | Plantation / Cultivation – Plantation / Cultivation | 3.315007 |
| 36 | Plantation / Cultivation – Water Body | 2.717629 |
| 37 | Plantation / Cultivation – Developed | 105.207248 |
| 38 | Plantation / Cultivation – Wetlands | 5.996488 |
| 39 | Plantation / Cultivation – Plantation / Cultivation | 9.009268 |
| 40 | Plantation / Cultivation – Water Body | 7.03309 |
| 41 | Plantation / Cultivation – Developed | 642.249834 |
| 42 | Plantation / Cultivation – Wetlands | 68.197762 |
| 43 | Plantation / Cultivation – Plantation / Cultivation | 1202.349855 |
| 44 | Plantation / Cultivation – Water Body | 6.184461 |
| 45 | Plantation / Cultivation – Developed | 100.545627 |
| 46 | Plantation / Cultivation – Wetlands | 5.676806 |
| 47 | Plantation / Cultivation – Plantation / Cultivation | 54.95272 |
| 48 | Wetlands – Water Body | 5.829465 |
| 49 | Wetlands – Developed | 8.124394 |
| 50 | Wetlands – Wetlands | 3.602929 |
| 51 | Wetlands – Plantation / Cultivation | 2.28844 |
| 52 | Wetlands – Water Body | 3.361341 |
| 53 | Wetlands – Developed | 17.66198 |

| | | |
|---|---|---|
| 54 | Wetlands – Wetlands | 8.08193 |
| 55 | Wetlands – Plantation / Cultivation | 8.951302 |
| 56 | Wetlands – Water Body | 2.439849 |
| 57 | Wetlands – Developed | 31.020847 |
| 58 | Wetlands – Wetlands | 58.643485 |
| 59 | Wetlands – Plantation / Cultivation | 98.381515 |
| 60 | Wetlands – Water Body | 5.613075 |
| 61 | Wetlands – Developed | 30.276737 |
| 62 | Wetlands – Wetlands | 12.89136 |
| 63 | Wetlands – Plantation / Cultivation | 29.682174 |

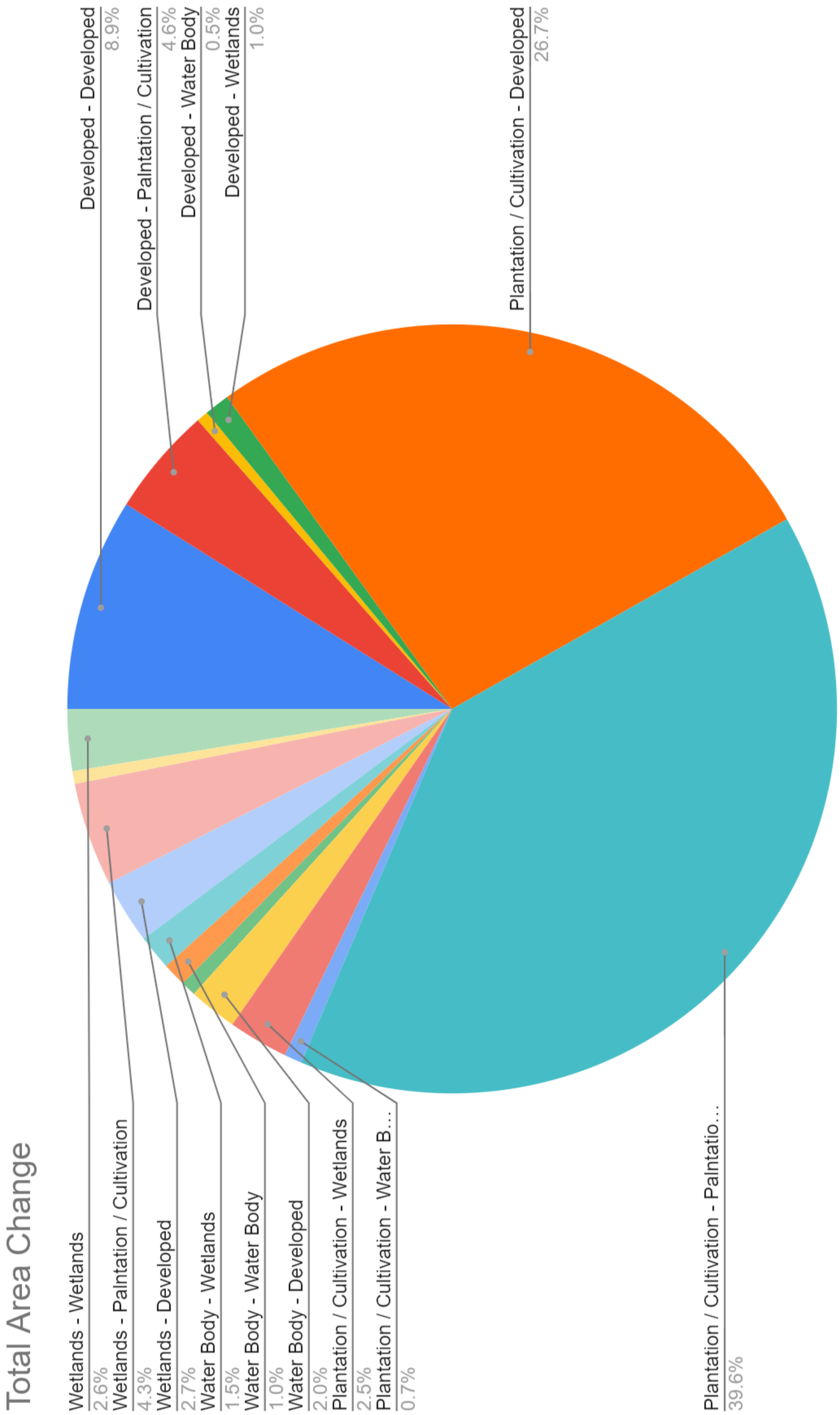


**Figure 4.10** A Pie Chart representing change in Total Area

**Table 4.4** Sum of the total area

| *Change* | Sum of Total Area |
|---|---|
| Developed – Developed | 286.011242 |
| Developed – Plantation / Cultivation | 146.842814 |
| Developed – Water Body | 15.728996 |
| Developed – Wetlands | 33.62086 |
| Plantation / Cultivation – Developed | 856.666121 |
| Plantation / Cultivation – Plantation / Cultivation | 1269.62685 |
| Plantation / Cultivation – Water Body | 23.599634 |
| Plantation / Cultivation – Wetlands | 80.631274 |
| Water Body – Developed | 65.288305 |
| Water Body – Plantation / Cultivation | 18.395748 |
| Water Body – Plantation / Cultivation | 1.727379 |
| Water Body – Water Body | 31.887739 |
| Water Body – Wetlands | 46.842093 |
| Wetlands – Developed | 87.083958 |
| Wetlands – Plantation / Cultivation | 139.303431 |
| Wetlands – Water Body | 17.24373 |
| Wetlands – Wetlands | 83.219704 |
| **Grand Total** | **3203.719878** |

Table 4.4 shows us the sum of the total area under observation. This comes to 3203.7198 square kilometers, which is the entire span of the study area.

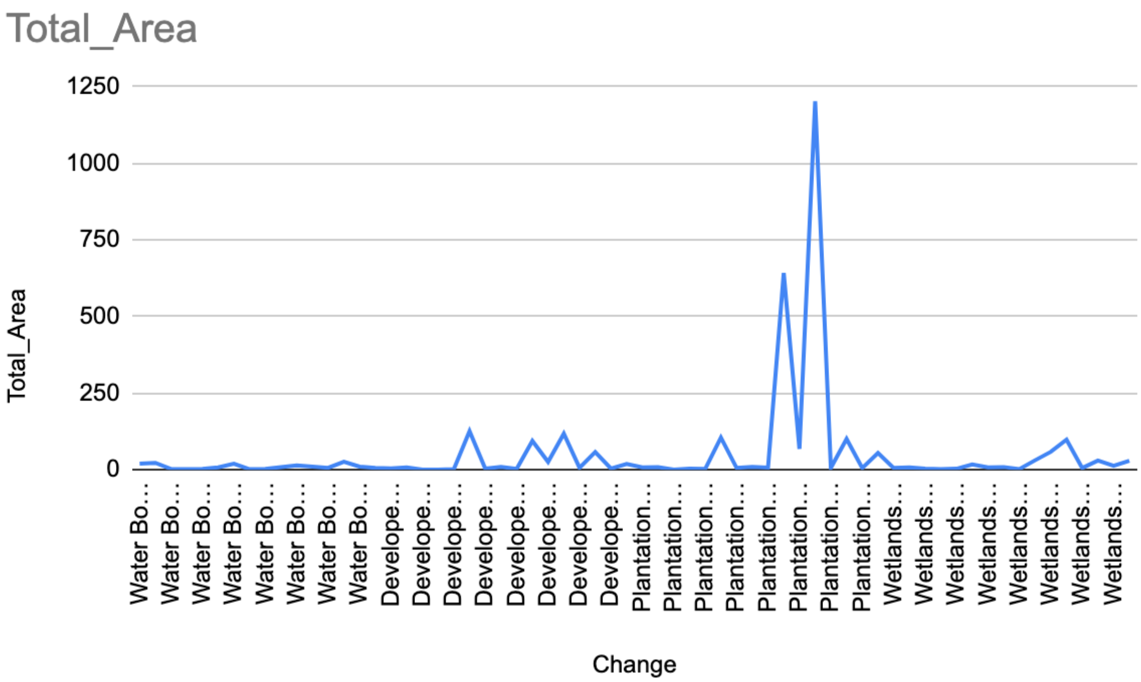


**Figure 4.11** A line graph showing the variation in the research region's total area

**Table 4.5** Temporal Change representation of features/attributes

| **Temporal Change (2002-2023)** | **Total Area Change** |
| --- | --- |
| Developed – Developed | 286.011242 |
| Developed – Plantation / Cultivation | 146.842814 |
| Developed – Water Body | 15.728996 |
| Developed – Wetlands | 33.62086 |
| Plantation / Cultivation – Developed | 856.666121 |
| Plantation / Cultivation – Plantation / Cultivation | 1269.62685 |
| Plantation / Cultivation – Water Body | 23.599634 |
| Plantation / Cultivation – Wetlands | 80.631274 |
| Water Body – Developed | 65.288305 |
| Water Body – Plantation / Cultivation | 20.123127 |
| Water Body – Water Body | 31.887739 |
| Water Body – Wetlands | 46.842093 |
| Wetlands – Developed | 87.083958 |
| Wetlands – Plantation / Cultivation | 139.303431 |
| Wetlands – Water Body | 17.24373 |
| Wetlands – Wetlands | 83.219704 |

### 4.4 Built Up Area

The urbanized region of all three timelines is shown in Figure 4.12. This figure represents the composite map of the complete developed area for all three timelines. In this figure, we can observe the change in area in the developed region. It clearly represents the surge in the built-up area through the timeline.

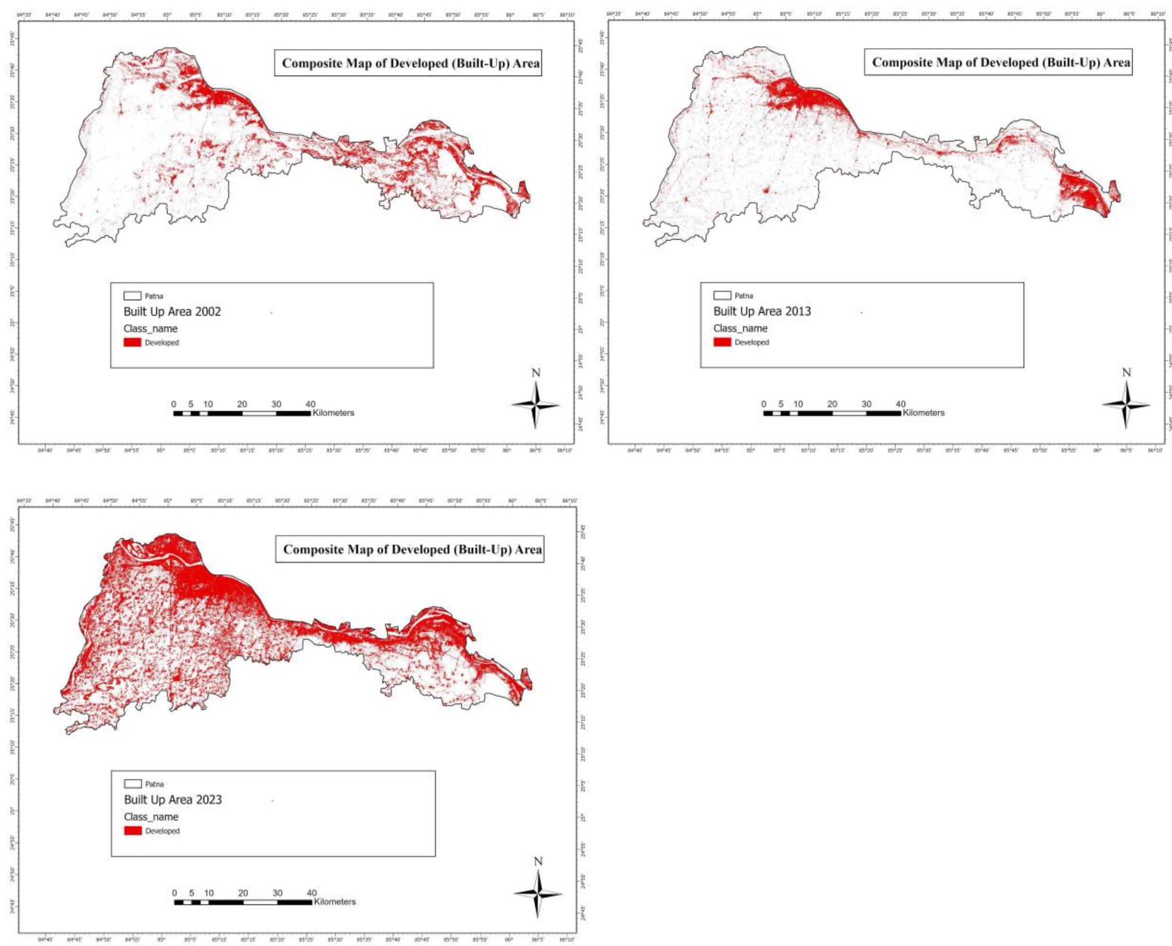


**Figure 4.12** Dynamics of change in Built-Up Area

The figure 4.13 represents the total built-up area of all the timelines in a combined manner. In this figure, the different built-up areas of different time zones are shown in different colors so that there is clarity in understanding the resulting image.

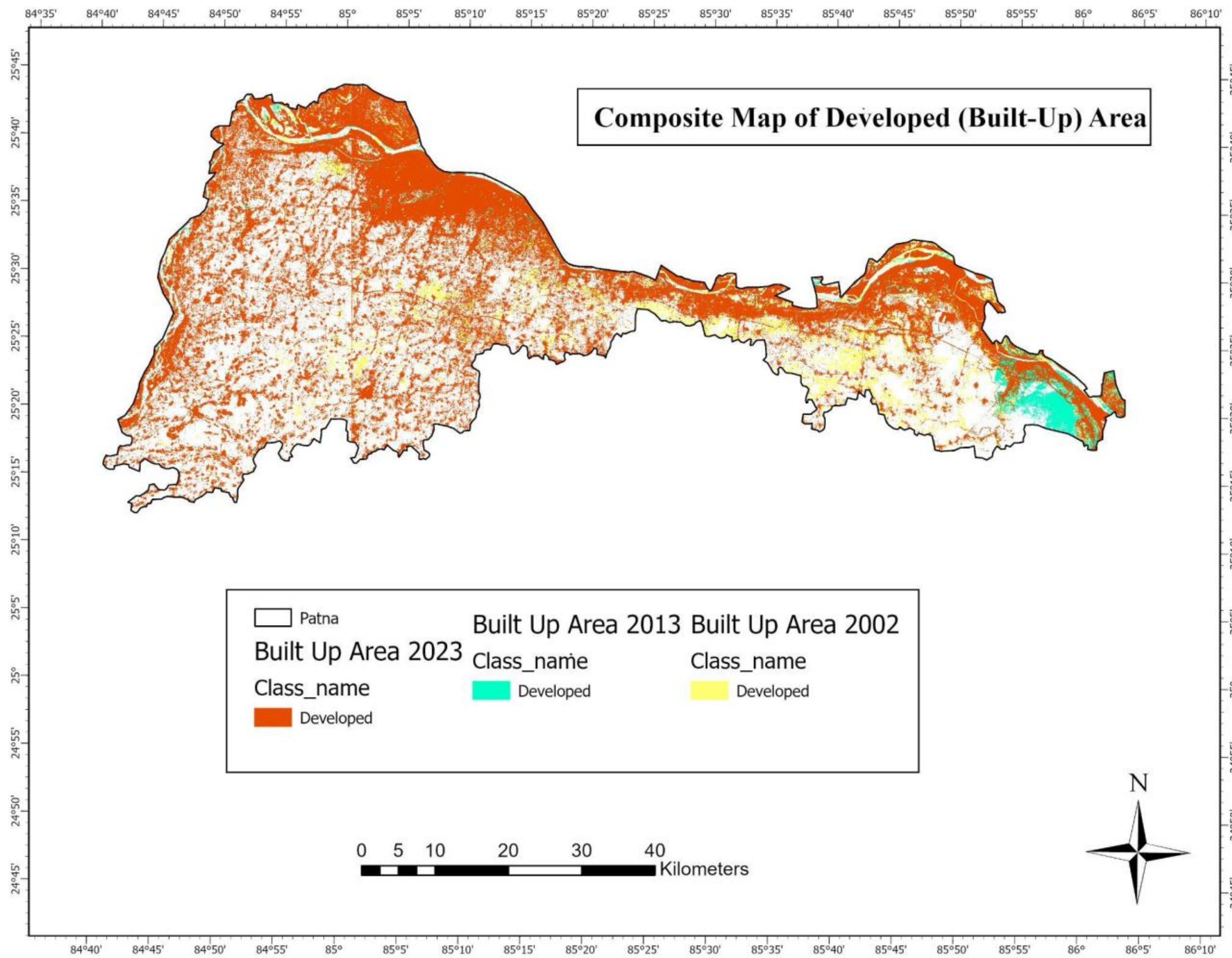


**Figure 4.13** Composite map of Built-Up Area of all three timelines combined

*CHAPTER 5*

# *CONCLUSIONS*

## 5.1 Summary and Research Analysis

This extensive and comprehensive research is done to investigate the spatio-temporal configurations of LULC alterations in Patna, the capital of Bihar and has undergone expeditious population outbursts and economic development during the past few decades.

The Land Use Land Cover maps were composed using Landsat 7 ETM+, Landsat 8 OLI, and Sentinel 2B satellite data. After the preparation of LULC maps, change detection was conducted. The results indicate that the LULC patterns of Patna have seen huge alteration during the study period.

The paramount conversion was noticed in the built-up domain, which saw an increase of 56.4%, followed by a decrease in all other parameters, i.e., water bodies, plantations, and wetlands.

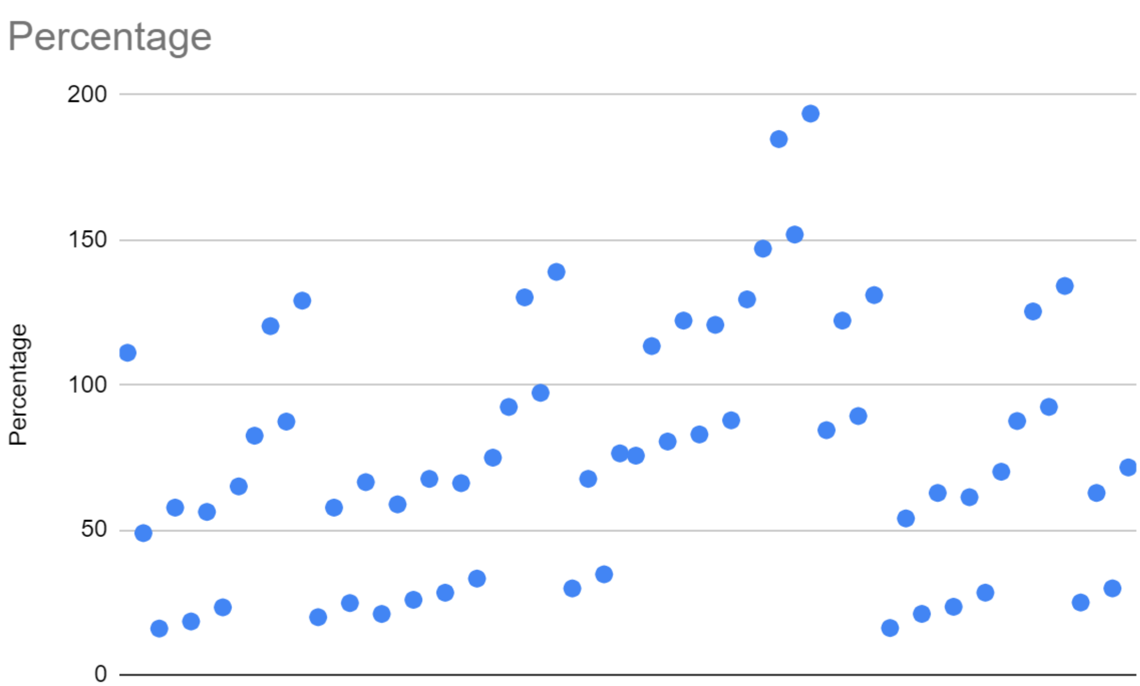


**Figure 5.1** Percentage of change in area of all features

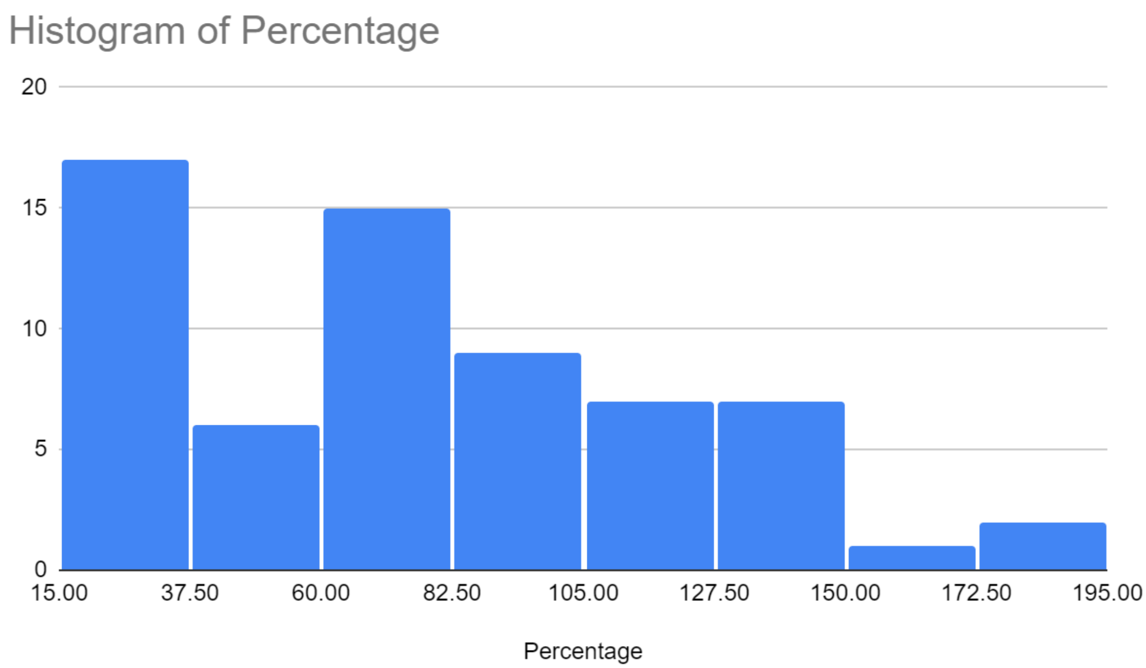


**Figure 5.2** Histogram of percentage of change in area

The urbanization seen is further intensifying with better transportation, infrastructural facilities, and transformation. Most of the transformation witnessed is from rural agrarian to urban markets. It has been observed that urban expansion is going on at a rapid pace. Despite this great venture of urbanization, the water bodies and vegetation of the city are witnessing constant decline in their areas. This depletion of water bodies and vegetation can have serious environmental impacts on the city.

For the sustainable growth of the city, open spaces must be used to develop urban greens. A plantation drive must be brought in for better air quality and to combat climate change issues.

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