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Multi-Temporal Image Processing for LULC Classification and Change Detection

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ABSTRACT

Changes in land use land cover (LULC) are critical in regional studies, local, and worldwide changes in the environment. The term "land use" relates to how humans are using the landscape, whether it is for expansion, conservation, or a combination of the two. Human activity on the Earth's surface alters the land cover area. These adjustments greatly affect how well-functioning vital Earth system components (such as the balance of energy, soil, and water). Applications for remote sensing make it possible to analyses land changes quickly and affordably. Numerous researchers have created techniques for analyzing modifications in the LULC. This study used GIS and random forest machine learning technique to pinpoint the LULC changes in Muzaffarpur District's urban and rural areas in the span of 15 years i.e., 2005 to 2020. The User land is scattered throughout the western region. The district's soil becomes more salinized and alkaline as a result of the waterlogging that is also prevalent in some areas of the district. This study's technique is simple and inexpensive. Between 2005 and 2020, there were major variations in the LULC in the research area. The rise in built-up activity is the main cause of the LULC alterations in the studied region. The current study may not be significantly impacted by the LULC changes. However, to maintain environmentally sustainable development in the future, LULC alteration needs to be continuously watched.

Keywords Multi-temporal analysis, change detection, Remote sensing, LULC classification; ArcGIS Pro, Machine learning.

INTRODUCTION

Changes in land use land cover (LULC) are critical in regional studies, local, and worldwide changes in the environment (Mas 1999, Gupta and Munshi 1985). The extent to which forests, wetlands, paved surfaces, agricultural, as well as other kinds of land and water cover the Earth's surface is referred to as land cover (Prakasam 2010). The term "land use" relates to how humans are using the landscape, whether it is for expansion, conservation, or a combination of the two. Recreational areas, wildlife habitats, agricultural land, and developed land are all examples of land use (Reis 2008). Over the past century, both human population and effect on the land have increased dramatically. Human activity on the Earth's surface alters the land

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cover area. These adjustments greatly affect how well-functioning vital Earth system components (such as the balance of energy, soil, and water). Additionally, the demand of a rising population on finite natural resources results in surface modifications coverage (Islam *et al.* 2018). Changes in LULC come from a variety of sources (Lambin *et al.* 2001). The primary causes of regional and global LULC changes are forest loss, agricultural growth, urbanization, and globalization (Aansen *et al.* 2014, Sahu *et al.* 2022, Rawat *et al.* 2021). The information required to understand the pattern in Land use changes in a coastal zone was highlighted by (Kaliraj *et al.* 2017). The LULC is always evolving and changing. LULC maps must be up-to-date and precise for efficient planning, monitoring global change, environmental sensing, and predicting forest degradation. Reports on changes to the LULC are essential for managing and using resources from nature. Resources from nature high and medium-resolution multispectral and multitemporal data from satellites is now accessible as critical instruments for assessing forest degradation, vegetation cover, and urban growth (Mustafa *et al.* 2007). Such an aim for examining landscape changes across the Earth's surface is made possible by remote sensing data and GIS techniques (Estoque and Murayama 2015). Traditional approaches such as field surveys, available data, and layouts are used for mapping. Traditional methods are therefore time-consuming and costly. Furthermore, in changing swiftly environments, the produced maps quickly become obsolete (Dash *et al.* 2015). Remote sensing data, as opposed toward the traditional data collecting techniques, delivers useful information quickly and inexpensively. Satellite with very high-resolution data or aerial photographs are essential for analyzing changes in LULC in metropolitan areas. However, these information sets are hard to come by because of cost limitations (Rawat and Singh 2022). However, a worldwide application of the Landsat Multi-Spectral Scanner (MSS), Operational Land Imager (OLI), and TM data sets were analyzed for LULC change detection (Raj *et al.* 2022). Using data from Landsat TM (Wang *et al.* 2009) assessed changes in China's bare soil, urban land, land beneath water bodies, and vegetation-coverage land. Odindi *et al.* (2012) observed changes in land usage in Port Elizabeth, South Africa, from 1990 to 2000 using Landsat TM information. Free access to Landsat information data is offered by http://earthexplorer.usgs.gov web platform. There are now several methods for evaluating and identifying LULC alterations. GIS and RS technology are two examples of effective techniques for obtaining timely and accurate information on trends in and changes to land usage (Arveti *et al.* 2016). Applications for remote sensing make it possible to analyses land changes quickly and affordably. Numerous researchers have created techniques for Analyzing modifications in the LULC (Singh 1989), including post-classification modifications in LULC, recognition of multi-temporal composite imagery changes, and programmed digitization of transformation, as well as vegetation index differencing (Belal and Moghanm 2011). The main involvement of this study is a quantitative measurement of the LULC in Muzaffarpur District and the area around it from using multi-temporal Landsat images from 2005 to 2020. Determining the impact of urbanization and climate conditions is the main goal of this study. Although previous research has helped to discover to discover LULC changes in the research region, this study combines GIS and remote sensing approaches. When evaluating vast quantities of picture data, the use of quantum-inspired image processing in urban surveillance is seen as critical.

MATERIALS AND METHODS

This paper focused on analyzing shifts in land use using demographic information and satellite information. In this experiment, the quantitative change detection method was used. Every satellite imagery is categorized using the change detection approach. Following classification, the generated Land use/cover maps are compared using a change detection matrix utilizing a pixel-by-pixel method. The following approach was used in this study: (1) Data collecting, (2) Image pre-processing, and (3) Image analysis. (4) Land use/cover classification technique, (5) Training data sample selection, (6) Classification of the image (7) Accuracy evaluation, and (8) Identifying changes. Except for the information collecting stage, all processes were completed using ArcGIS Pro.

Image classification

Landsat imagery from various time periods were utilized to investigate and categories the land cover types in the research region. Machine learning was used to classify the data. Random forest is a popular supervised machine learning strategy for classification and regression problems. It constructs decision trees from several samples, using their mean for regression and majority vote for classification. One of the Random Forest Algorithm's most important features is its ability to handle big datasets with both continuous variables, as in regression, and categorical variables, as in classification features. It performs better than competing algorithms in classification issues. The spectral signature files made for every class were utilized for categorization.

According on the dates they were received, the Landsat information are categorized. To lessen the salt and pepper effect, the categorized data was subsequently put through a dominant filter with a 4 × 4 size kernel (Kantakumar *et al.* 2016). The LULC categories of the research area are depicted in the bulk of the categorized images produced by the filter. The classified photos were compared to one another in order to assess how the LULC pattern varied over time.

Classification accuracy assessment

The validity of the classified images was calculated using Google Earth Pro after they were generated. Following image classification, it is necessary to assess classification accuracy. The equalized stratified random tool was used to generate random points in ArcGIS Pro, which were then transformed into a kml file for comparison on Google Earth Pro. The software recognized each point's distinct color and number of pixels automatically. As references, the classes in the categorized picture were utilized. The user then manually assigned the corresponding class to the randomly generated points. For the classified imagery, the error matrix and kappa statistics were calculated using ArcGIS Pro's compute confusion matrix tool. This procedure was carried out on four classified images (i.e., 2005–2020). The classification accuracy is indicated by the error matrix (Foody 2002). In contrast to the rows, which show the classes that formed as a result of classifying the image. The columns display the classes that the user has selected determined based on the reference values. The error matrix's diagonal cells represent the total number of successfully detected pixels for each reference and categorized data category. The off-diagonal cells, which highlight a mismatch between reference and classified information, display the incorrectly classified pixels. Omission mistakes and commission errors can happen throughout the classification process.

When a categorization mechanism allocates pixels to a category when they don't fit there, errors of commission occur. Above and below the main diagonal in column cells, it was found how many pixels were mistakenly classified as belonging to a certain class. The number of commission errors was also mentioned in the Producer's accuracy. When pixels from one class are used in another, there are errors of omission in all of the classes. In the confusion matrix the number of blank pixels were discovered inside the row cells to the left and right of the primary diagonal. Another factor that characterizes omission errors is the user's accuracy. The set of equations were used to determine the producer's accuracy (Pa) and the user's accuracy (Ua):

$$\text{Pa}\ (\%) = \left(\frac{X_{kk}}{x_{+k}}\right) \quad (1)$$

$$\text{Ua} = \left(\frac{X_{kk}}{x_{+k}}\right) \times 100\% \quad (2)$$

The kappa coefficient (k) was calculated using the formula below.

$$\text{Kappa coefficient (k)} = \frac{N\sum_{k=1}^{r} - \sum_{k=1}^{r} (X_{k+} \cdot X_{+K})}{N^2 - \sum_{k=1}^{r} (X_{k+} \cdot X_{+K})} \quad (3)$$

N denotes the overall no. of pixels, r the no. of classes, and X_{kk} the total number of pixels in row "k" & column "k," In the confusion matrices, X_{k+} denotes the entire values in row "k" and x_{+k} denotes the entire values in column "k".

Change detection

Because of their low cost and excellent temporal resolution, RS and GIS based change detection methods are commonly employed. The most popular method for spotting LULC changes is the post-classification assessment methodology, which is dependent on random Forest-Machine learning classification.

For a wide range of information, this approach has produced good classification accuracy overall (Muttitanon and Tripathi 2005). The post-classification comparison method compares the associated classes after classifying photos to find regions of change. The post-classification assessment provided the highest classification accuracy when different approaches were evaluated. In order to confirm Changes in LU in the Datong basin, China, (Sun and Wang 2009) used Landsat data as well as a using the MLC algorithm for post-classification comparison. In this study, the effects in LULC were estimated using two registered and independently categorized data. The precision of the thematic maps produced by picture categorization determines the correctness of the outcomes. Each class's degree of change (C) was computed with the following formula:

$$C_i = L_i - B_i \tag{4}$$

The percent variation (C%) for each specific surface area was calculated using a simple algorithm that divided the changes in a class by the service area in the reference year and multiplied by 100.

$$P_i = \frac{L_i - B_i}{B_i} \times 100 \tag{5}$$

Where: Ci = Amount of variation in class 'i', I = The number of classes in an imagery, Pi = Variation in Class 'i' as a Percentage, Li= Base imagery (2005), and Bi = Newest image (2020).

Study area

This study used GIS and remote sensing technology to pinpoint the LULC changes in Muzaffarpur District's urban and rural areas (Fig. 1). The study region is situated between latitudes 25^{0}54'00" and 26^{0}23'00" north and 84^{0}53'00" and 85045'00" east. The city is located in a seismically active region of India. This low-centered, saucer-shaped settlement is situated on a bed of Himalayan sand and silt that was transported by the glacier- and rain-fed meandering rivers of the Himalayas to the vast Indo-Gangetic plains of Bihar.

Muzaffarpur District has 4,801,062 residents, this is about similar to the population of Singapore or the state of Alabama in the United States, according to the 2011 Census. It now occupies the 24th spot in India (out of a total of 640). There are 1,514 inhabitants per square kilometer in the district (3,920 people per square mile). Its population increased by 28.14% between 2001 and 2011. With a literacy rate of 63.4%, Muzaffarpur has 900 girls for every 1000 men. The population of scheduled castes and tribes is 15.66% and 0.12%, respectively.

Fig. 1. Study area.

The district experienced 1280 mm of rainfall on average. The monsoon season is well known to occur from June through September. According to monthly rainfall data, the monsoon season accounts for 85% of total precipitation. The district receives the most rainfall during the southwest monsoon season and a small amount during the northeastern monsoon season.

Alluvium covers the entire district. There are generally four different types of soil in this area. They are divided into four categories: Sandy loam, clayey, clay soil with sand admixture known as Banger, and lastly, patches of User land with salt efflorescence's known in local languages as rah. The sandy loam variation predominates in the area south of the Burhi Gandak River. The northern region is home to Banger and clayey soils. The User land is scattered throughout the western region. The district's soil becomes more salinized and alkaline as a result of the waterlogging that is also prevalent in some areas of the district.

Table 1. Kappa coefficient for the year 2005.

Class Value	Water	Trees	Agriculture land	Urban area	Barren land	Scrub	Total	User accuracy
Water	20	0	0	0	0	0	20	1
Trees	0	19	0	1	0	0	20	0.95
Agriculture land	2	0	16	0	2	0	20	0.8
Urban area	1	0	0	18	1	0	20	0.9
Barren land	1	0	1	3	14	1	20	0.7
Schrub	0	4	1	0	0	15	20	0.75
Total	24	23	18	22	17	16	120	
Producer accuracy	0.83	0.83	0.89	0.82	0.82	0.94		
Kappa				**0.82**				

Table 2. Kappa coefficient for the year 2010.

Class value	Water	Trees	Agriculture land	Urban area	Barren land	Scrub	Total	User accuracy
Water	20	0	0	0	0	0	20	1
Trees	0	20	0	0	0	0	20	1
Agriculture land	0	0	17	0	3	0	20	0.85
Urban area	0	0	0	18	2	0	20	0.9
Barren land	0	0	0	5	15	0	20	0.75
Schrub	0	4	0	0	1	15	20	0.75
Total	20	24	17	23	21	15	120	
Producer accuracy	1	0.83	1	0.78	0.71	1		
Kappa				**0.85**				

RESULTS AND DISCUSSION

Muzaffarpur District data sets (Landsat 5 for 2005, 2010, and Landsat 8 for 2015 and 2020) were registered in ArcGIS Pro. Using latitude and longitude information to georeferenced the photos from the investigation region's previously georeferenced SOI topo sheet, the data sets were registered. All data sets were registered, and then visual interpretation was trained on them. The discovered classes were digitally represented by polygonal drawings to produce signature files. The signature file was then used to create the LULC maps utilizing Random Forest classification. Tables 1–4 display the information sets' accuracy evaluation results. The region occupied over a five-year period by different classes was calculated using the attribute table. A LULC map from one data set and a LULC map from another were compared after image categorization using the post-classification comparison method. The comparison displays the variations that acquired place over the course of the five-research period numerically. Following image

Table 3. Kappa coefficient for the year 2015.

Class value	Water	Trees	Agriculture land	Urban area	Barren land	Scrub	Total	User accuracy
Water	20	0	0	0	0	0	20	1
Trees	0	19	1	0	0	0	20	0.95
Agriculture land	0	0	20	0	0	0	20	1
Urban area	0	0	0	19	0	1	20	0.95
Barren land	0	0	1	3	16	0	20	0.8
Schrub	0	0	3	1	2	14	20	0.7
Total	20	19	25	23	18	15	120	
Producer accuracy	1	1	0.8	0.83	0.89	0.93		
Kappa				**0.88**				

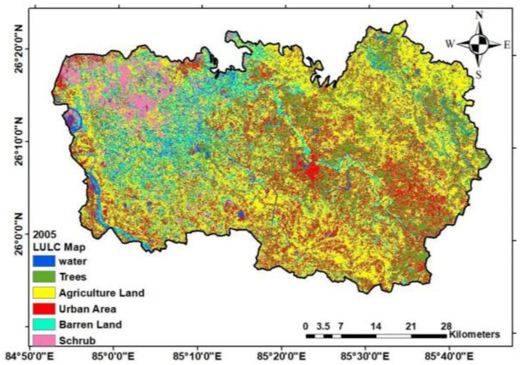

Fig. 2. LULC map for 2005.

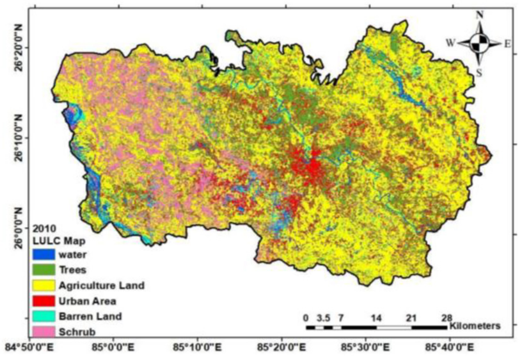

Fig. 3. LULC map for 2010.

categorization, maps with a 1: 50,000 scale were produced using ArcGIS Pro.

LULC trend of Muzaffarpur District in 2005

Figure 2 show LULC based on Landsat 5. Table 1 lists the land types for the year 2005 along with related information. The category with the largest size was agricultural land (1202.70 km^2, or 37.75% of the total area), while the second largest category was trees (814.07 km^2, 25.55% of the whole area). Urban area (352.39 km^2, 11.06% of the whole area), barren land (322.38 km^2, 10.12% of the whole area), shrub (189.88 km^2, 5.96%), and water (304.74 km^2, 9.56% of the whole area) made up the rest of the land use categories.

LULC trend of Muzaffarpur District in 2010

The Landsat 5 data collection was used to create the categorized image for 2010 (Fig. 3). Results from 2010 show that trees made up the majority of the land area, accounting for 544.81 km^2 (or 17.10% of the whole area), followed by agricultural land (1450.13 km^2, or 45.51% of the whole area). Urban area (427.91 km^2, 13.43% of the total area), schrub (457.12 km^2, 14.35% of the whole area), barren land (162.06 km^2, 5.09% of the whole area), and water bodies (144.13 km^2, 4.52% of the whole area) have been the four land-use groups. Table 2 lists the landuse classifications for 2018 along with related information.

LULC trend of Muzaffarpur District in 2015

The Landsat 8 data collection was used to create the categorized image for 2015 (Fig. 4). The results showed that agricultural land (1506.30 km^2, or 47.28% of the total area), followed by urban area (727.07 km^2, or 22.82% of the total area), was the dominant proportion. Trees (369.70 km^2, 11.60% of

Table 4. Kappa coefficient for the year 2020.

Class value	Water	Trees	Agriculture land	Urban area	Barren land	Scrub	Total	User accuracy
Water	20	0	0	0	0	0	20	1
Trees	0	19	0	1	0	0	20	0.95
Agriculture land	2	0	16	0	2	0	20	0.8
Urban area	1	0	0	18	1	0	20	0.9
Barren land	1	0	1	3	14	1	20	0.7
Schrub	0	4	1	0	0	15	20	0.75
Total	24	23	18	22	17	16	120	
Producer accuracy	0.83	0.83	0.89	0.82	0.82	0.94		
Kappa				**0.82**				

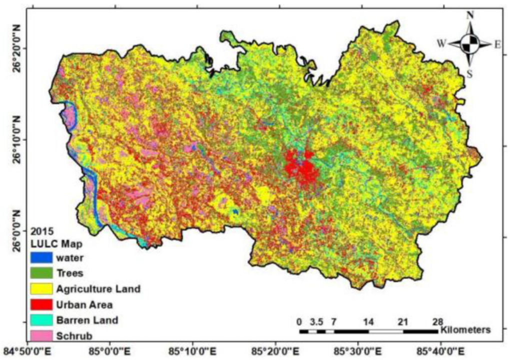

Fig. 4. LULC map for 2015.

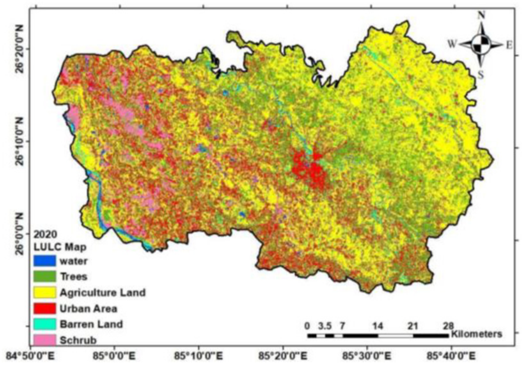

Fig. 5. LULC map for 2020.

the total area), barren ground (198.58 km^2, 6.23% of the whole area), schrub (276.25 km^2, 8.67%), and water (108.27 km^2, 3.40% of the whole area) made the rest of the land use groups.

LULC trend of Muzaffarpur District in 2020

The using Landsat 8 set of data, the categorized image for 2020 (Fig. 5) was created. The data show that urban area (1140.05 km^2, 35.78% of the total area) is second in size to agricultural land (1361.85 km^2, 42.74% of the total area). Trees (308.92 km^2, 9.70% of the total area), schrub (195.64 km^2, 6.14% of the total area), barren ground (129.31 km^2, 4.06%) and water (50.41 km^2, 1.58% of the whole area) made the rest of the land use groups.

Images from the years 2005, 2010, 2015, and 2020 with a kappa coefficient

For the LULC map data from 2005, 2010, 2015, and 2020, an accuracy evaluation was done. The kappa value for the 2005 LULC map was 0.82 (Table 1). The producer's accuracy is above or equal to 80% for each class. For four categories (water, trees, agricultural land, and urban area), the UA was > 80%. The user accuracy for the groups scrub and barren land is 0.70 and 0.75, respectively. The kappa value for the 2010 LULC map was 0.85 (Table 2). For all classifications other than metropolitan areas and arid land, the producer's efficiency was greater than 80%. With the exception of scrub and waste land, the UA was more than in all categories 80% The kappa value for the 2015 LULC map was 0.88. (Table 3). For all categories, the PA was more than 80%. In all classes other than scrub, the UA was greater than 80%. The kappa value for the 2015 LULC map was 0.82 (Table 4). For all classes, the Pa exceeded 80%. With the exception of brush and waste land, the user's accuracy was more than 80% in completely categories.

Change detection from 2005 to 2020

Table 5 displays the area under the land cover classes

Table 5. Land use/Land cover area (km^2).

Type	2005	2020	Area Changed (Km^2) (2020–2005)	Percent change %
Water	304.73	50.40	254.33	7.98
Tress	814.07	308.92	505.15	15.85
Agriculture	1202.70	1361.85	-159.15	-4.99
Urban area	352.39	1140.05	-787.66	-24.72
Barren land	322.38	129.31	193.07	6.06
Schrub	189.88	195.64	-5.75	-0.18

Note: (+) Denotes an increase, while (-) denotes a decrease in the area covered by a LULC class over a 15-year period (2005–2020).

and its variations from 2005 to 2020. Over a period of 15 years, both positive and negative developments were seen the area covered by the LULC classes. The areas of the categories for water bodies, trees, and arid land all decreased, whilst the categories for agricultural and urban areas increased. According to Table 5 the categories of land in urban areas experienced the largest changes in area, followed by the categories of trees.

Table 5. represents the area covered by separately LULC classification in the 2005 and 2020 data sets as well as variations in each class's range over a 15-year period (in Km^2 and %).

Water area

From 9.56% of the entire land region in 2005 to 1.58% of the entire land region in 2020, the covered area by water area has reduced. The region that was occupied by water bodies decreased as a result of the transformation of water bodies from other land and the forty-year decline in rainfall at examined location.

Agriculture

The area used for agriculture increased from 37.75% of the entire land surface in 2005 to 42.74% of the total land surface in 2020. During the observation period, the quantity of agricultural land surface in the study area rapidly increased. Due to the decrease in forest cover within the study area and the transformation of some arid terrain into agricultural land, the total area by agriculture expanded.

Urban region

From 11.06% of the entire land region in 2005 to 35.78% of the entire land region in 2020, more land fell into the urban classification. Due to the expansion in tourism, population growth, and housing needs, the area designated as urban expanded.

Trees

The area under the tree's category decreased significantly from 25.55% of the total area in 2005 to 9.70% of the total area in 2020. The loss of forestland is a result of its transformation into developed areas like parks, highways, and parking lots. The decline may also be a result of the utilization of forest area for other types of growth.

Barren land

From 10.12% of the total land surface in 2005 to 4.06% of the entire land surface in 2020, the area covered by bare land and other land increased. Due to the conversion of some barren areas into settlement and agricultural area, there is a decline in barren land as well as other land.

Conclusion and future scope

GIS and Remote sensing techniques were used in this study to quantify and understand LULC changes in Muzaffarpur District across a 15-year period, from 2005 to 2020. This study's technique is simple and inexpensive. Using multi temporal satellite imagery, the scope of land-use changes in Muzaffarpur District has been determined. In this research, the confusion matrix was utilized to test classification accuracy. This study's accuracy in classification was appropriate. Between 2005 and 2020, there were major variations in the LULC in the research area. The region covered by buildings expanded greatly throughout these 15 years, while the area covered by trees, arid ground, and water bodies dropped sharply. The rise in built-up activity is the main cause of the LULC alterations in the studied region.

The current study may not be significantly impacted by the LULC changes. However, to maintain environmentally sustainable development in the future, LULC alteration needs to be continuously watched. In order to increase the system's efficacy, the work may also be expanded by using additional machines and deep learning methods like R-CNN and CNN.

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