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Detection and prediction of LULC change matrix in Gaya city using CA-Markov chain model

Alok Kumar Dubey*, Bihar; Firdaus Fatima Rizvi, Bihar; Akash Tiwari, Haryana

Abstract

The objective of this paper was to analyse the LULC change between the years 2000 and 2022 in Gaya City of Bihar and predict a change in LULC for the year 2030. The study tested the LULC change with the help of the Land Change Modeller technique and the prediction of LULC change has been made using the CA-Markov Chain model. The study is based on an extracted area of 4769 hectares of Gaya city. The study finds that 58 percent of the land under agriculture is lost during the 22 years preceding 2022; despite the addition to this class from other land-use categories mainly on account of expansion of the built-up area. This trend is predicted to continue in the future as well albeit at a slower pace. As food security depends on urban and peri-urban agriculture, this shrinkage in agricultural land may result in increasing food insecurity, loss of livelihood for the farmers, environmental degradation, sustainability of the city, etc. To ensure food security for all, existing agricultural productive land needs to be protected. Appropriate policies need to be framed and rigorously implemented to protect agricultural land from incessant urban expansion.

Keywords: *Agricultural land, land use land cover (LULC), remote sensing, prediction, CA-Markov chain model*

Introduction

Land cover is the physical material at the surface of the earth such as vegetation, water bodies, barren land, built-up area, etc whereas land use is the description of how people utilise the land for socio-economic activities such as commercial land, agricultural land, forested area, industrial area, etc as defined by the Food and Agriculture Organization (FAO), 2005.

It is well-known that the number of cities as well as their inhabitants are increasing rapidly all over the world engendering significant changes to land use land cover (LULC) of the cities and the surroundings adversely affecting the environment and ecosystem of many areas (Dewan & Corner, 2014; Xiuwan, 2002). Needless to emphasise, much of this expansion takes place in the peri-urban areas. Built-up area expansion on the outskirts of cities has a significant adverse impact on agricultural land resulting in a sharp decline in food production and affecting the livelihood of farmers (Zhou *et al.*, 2022, Pandey & Seto, 2015, Dewan & Yamaguchi, 2009, Fazal, 2000). It is imperative therefore to constantly monitor the quantity and quality of these changes and predict the future direction so as to influence public policy and

Table 1: Description of the dataset

Date	Satellite type	Path/Row	Resolution	Cloud cover
31-01-2000	Landsat-5 TM	141/043	30×30 meter	Less than 20%
12-02-2022	Landsat-8 OLI-TIRS			

Source: USGS Earth Explorer

their effective implementation. The broad aim of this research hinges on this aspect of LULC changes taking place in the Gaya city of Bihar.

LULC change detection measures urban dynamics. Changes in urban land use and land cover can be determined with the help of field surveys and a Geographical Information System. A field survey requires much time, labour, and money and cannot be conducted over a vast area whereas GIS with the help of remotely sensed data provides accurate and current information about changes. The changes between two different periods can be measured by techniques like Post Classification Comparison (PCC), image differencing, and Land Change Modeller (LCM) in GIS and RS. In this study, the Land Change Modeller (LCM) technique has been used with the help of IDRISI Selva software for better accuracy. The CA\Markov technique has been used in this study for predicting the change in LULC because it is the only tool to predict LULC for the future by using two independently classified images two different times. This method also provides a separate image of change (Gidey *et al.*, 2017).

Study area

Gaya is the second most populated city in Bihar after Patna (Fig. 1). According to the city development plan, 2010, the population is expected to increase by 48 percent by the year 2021 and by 80 percent by the year 2030 on the population base of 2001. In order to assess the impact of the growing population and the resultant changes in the LULC pattern, delineated 4769 hectares area of Gaya city was selected for the study. Geographically, this area is the northern extension of the Rohtas Plateau. The city is surrounded by hills on three sides and the river Phalgu flows on the fourth side of the city. Due to scanty rainfall received during the rainy season, the river becomes dry and converts into barren land for most part of the year.

The main objective of this paper is to analyse the LULC change between the years 2000 and 2022 in Gaya City of Bihar using GIS and RS and predict the LULC changes for the year 2030. For this analysis, remotely sensed data of the respective years have been used and image classification has been done by using the ESRI software ArcMap 10.8. User accuracy, producer's accuracy, overall accuracy, and Kappa Coefficient have been applied to test the accuracy of the LULC classification (Hütt *et al.*, 2016).

Database and Methodology

Database

Remotely sensed data has been obtained from an open-access platform, USGS Earth Explorer. For the year 2000 Landsat-5 TM (Thematic Mapper) has been used and for the year 2022, Landsat-8 OLI-TIRS (Operational Land Imager- Thermal Infrared Sensor) images have been obtained. Downloaded images have a 30×30-meter resolution and Path and Row are 141 and 043 respectively The datum of each image is WGS_1984

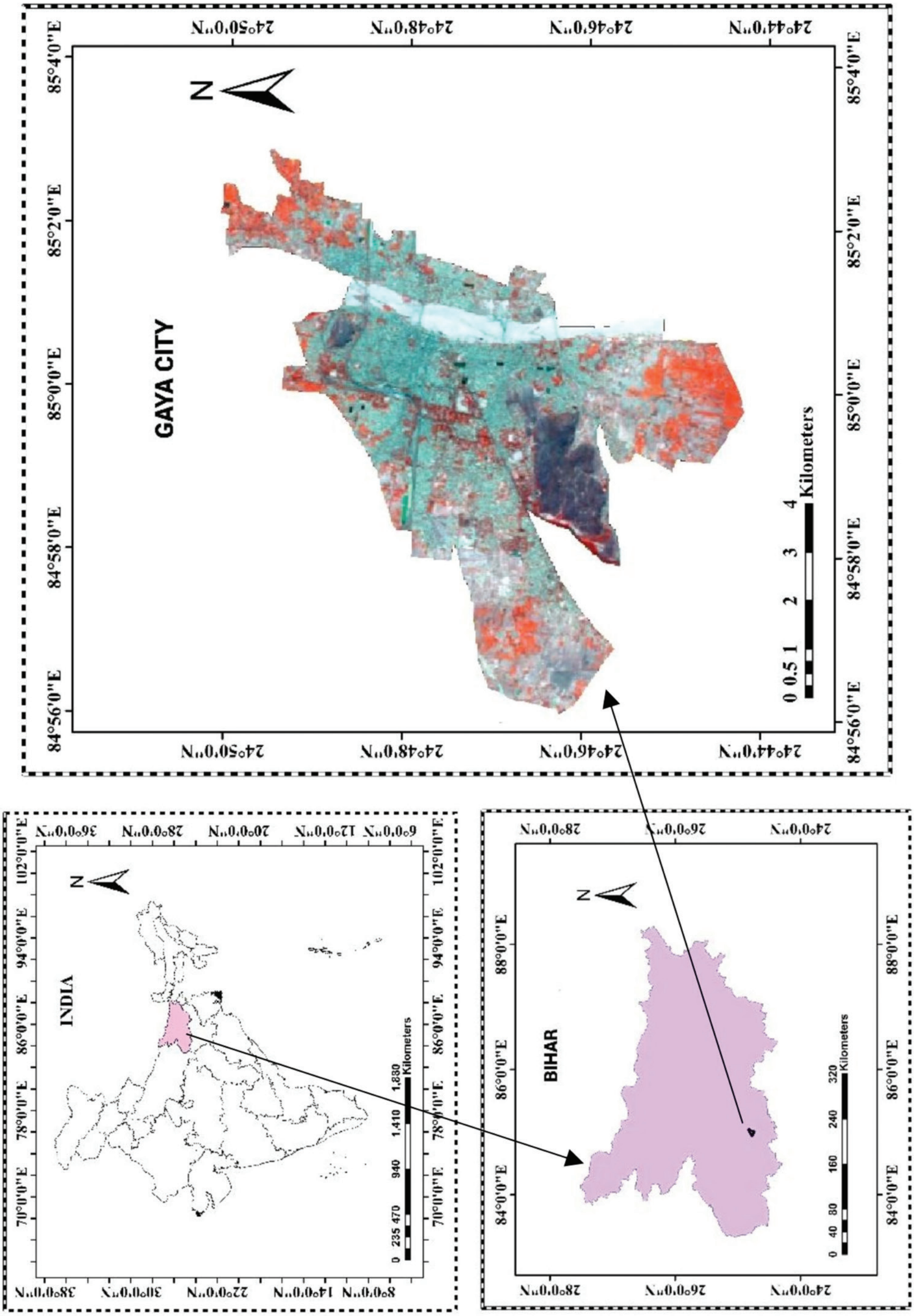

Fig. 1: Location of Gaya City

Source: Generated through GIS

and the coordination system is Universal Transverse Mercator zone 45 north. Before downloading images, cloud cover has been reduced to 0-20 percent. All seven bands have been used to create a composite image.

Image classification and accuracy assessment

For the LULC classification and to see the impact of the expansion of an individual legend on other legends, a shape file of the city has been digitized from the city master plan 2030. To identify the desirable objects of the natural world on a composite raster image, the image enhancement tool is used from the image analysis window, and for more clarity; the Symbology was changed several times during the selection of training samples. After the selection of appropriate numbers of training samples, the Maximum Likelihood Classification (MLC) algorithm has been applied to classify the images into desirable LULC categories. User's accuracy, Producer's accuracy, and Overall accuracy have been calculated for each image to test the accuracy level of classification. (Fig. 2) A random point selection method has been operated and a Google Earth Pro image was taken as the reference image. The Kappa coefficient is also calculated based on the Error Matrix.

The classification scheme of the image has been described in table 2 having five LULC categories that include water bodies, agricultural land, forested area, barren land, and built-up area.

Cellular Automata-Markov Chain Integrated Model

Markov-Chain Model

Markov Chain models are stochastic models that predict the probability of future land use change based on past trends. They use a series of random values to estimate the probability for a defined period by analysing previous values. The projection of future LULC maps is achieved using a LULC transition probability matrix that represents the likelihood of change from one period to another. A probability matrix is a collection of conditional probabilities that indicate the likelihood of a cell changing from one class to another during a defined interval.

The following equation represents the formula used in the Markov Chain model.

$$P_{(n+1)} = m_{ij} \times P_n \tag{1}$$

$$m_{ij} = \begin{bmatrix} m_{11} & m_{12} \dots m_{1p} \\ m_{21} & m_{22} \dots m_{2p} \\ \vdots & \dots \quad \vdots \\ m_{p1} & m_{p2} \quad m_{pp} \end{bmatrix} \tag{2}$$

In the equation (1), $P_{(n+1)}$ and Pn, represent the LULC at time span n and (n + 1) respectively. Here,

$0 \leq m_{ij} \leq 1$ and $\sum_{j+1}^{p} m_{ij} = 1, (i, j = 1,2, \dots \dots p)$

represent the transition probability matrix.

Initially, the LULC map was in .img file format that was converted to .rst file format for processing the data. The Markov Chain model was executed on IDRISI Selva 17.0 to analyse the LULC map between the years 2000 to 2022. A projection for a further eight years was made from the second LULC map (2022). Prediction of LULC has been made for the year 2030 because a bigger interval between the reference year and year chosen for prediction may lead to a higher chance of over-generalization. The background cell option was assigned as 0.0 and the proportional error was set to 0.15. The model generated a transition probability matrix in text format. The study generated three key

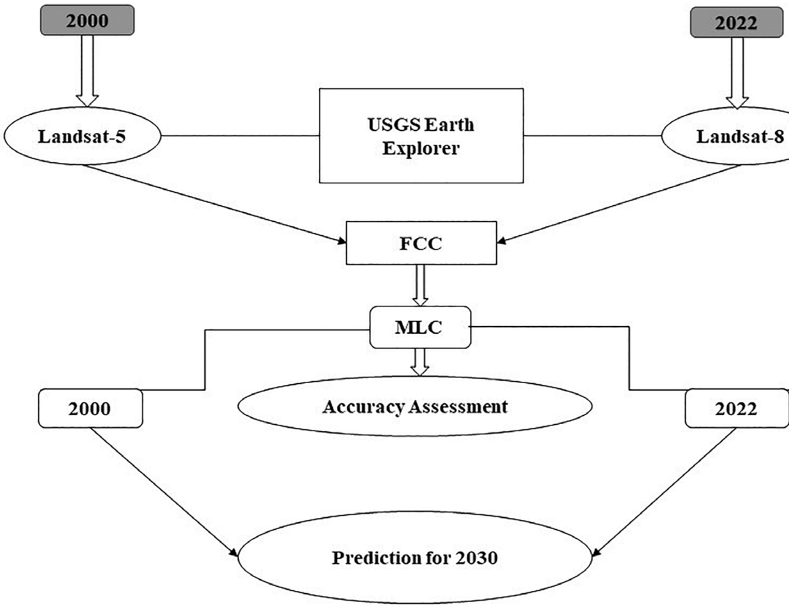

Fig. 2: Overview of methodology

outputs for the five LULC classes: a transition probability matrix, a transition areas matrix, and a set of conditional probability images for all land use classes.

Cellular-Automata Markov Chain Integrated Model

The Cellular Automata (CA) and Markov Chain models are reliable for predicting transitions between LULC types. The CA Markov model combines the benefits of both models and has been widely used to predict future LULC patterns. This model incorporates spatial adjacency and knowledge of the likely spatial distribution of transitions. A predefined standard contiguity filter of 5×5 was used to define the neighbourhoods of each cell and create spatially explicit contiguous weighing factors. The study used ten CA iterations to ensure reliable prediction of future LULC patterns.

$$5 \times 5 \text{ Contiguity Filter} = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

The CA-Markov Chain Model is a dynamic and integrated process that controls the predicting algorithm of a set of LULC classes. This model is best for predicting the pattern of the phenomenon (Gidey *et al.*, 2017). Looking at these advantages, this study used the CA-Markov Chain model to predict the LULC of the study area for the year 2030.

Result and discussion

LULC, 2000 and 2022

LULC in Gaya city has been analysed (Fig. 3a and Fig. 3b) based on the maps prepared for the purpose for the years 2000 and 2022.

Table 2: LULC for Gaya

LULC classes	Description
Water bodies	River, ponds, and other water patches.
Agricultural land	The area is being used for agricultural purposes.
Forested area	City forest, parks, private gardens, vegetation over hills.
Barren land	Sandy areas of the river channel exposed land with no vegetation.
Built-up area	Roads, railway lines, buildings, and other permanently paved and impervious surfaces.

Water bodies: As is already mentioned earlier monsoon is the main driver for recharging water bodies in Gaya city. It is evident that the area under water bodies has seen a significant decline in the period 2000-2022; from 150 hectares (3.15%) to 125 hectares (2.62%) respectively. It is clearly visible from LULC Fig. 3a and Fig. 3b that due to insufficient rainfall, the maximum area of the channel of the Phalgu River is seen as barren land.

Agricultural land: Due to urban expansion and human activities, the agricultural area is the most affected land use class. In both successive images, urban encroachment over agricultural land can be seen clearly. This is the only category that has shrunk most sharply over the study period. In the year 2000, the total agricultural land was 1908 hectares (40%) which is the maximum in all five categories for the study year 2000. Later, with the increment in population and the built-up area, the area under agriculture squeezed to 810 hectares (17%) by the year 2022. The loss of agricultural land is about 58 percent during the reference period.

Forest: The forested area or vegetation cover is the second major reflection of the rainfall. Two or three consecutive seasons of good rainfall might turn barren lands into vegetative areas and a few seasons of droughts or low precipitation could transform the forested area into barren or exposed areas. This is true of Gaya City and its surroundings. The Forested area was 255 hectares (5.35%) in the year 2000 which increased to 694 hectares (14.20%) by the year 2022. However, this increase is not due to an increase in rainfall but the result of the government programmes launched on the conservation of water and forest (*Jal Jeevan Hariyali Mission*) and the campaign on planting trees (*Shanti Vriksha*) implemented by the Department of Forest, Gaya. Under this campaign, 2.5 Lakh trees were planted in the district (Times of India, 2001).

Barren land: Area under barren land to responds to the factor of rainfall. The few seasons with better rainfall might make the barren land more suitable for agriculture or turn into tree coverage or forested areas. This phenomenon has occurred in Gaya City and its surroundings. The barren land area was 913 hectares (19.15%) in the year 2000, which decreased to 580 hectares (12.20%) in the year 2022. This barren land lies within the channel of the Phalgu River- a fact mentioned earlier.

Built-up area: This land use category, as expected, has increased sharply throughout the reference period on account of continuous increment in the population, public infrastructure, and private residences resulting

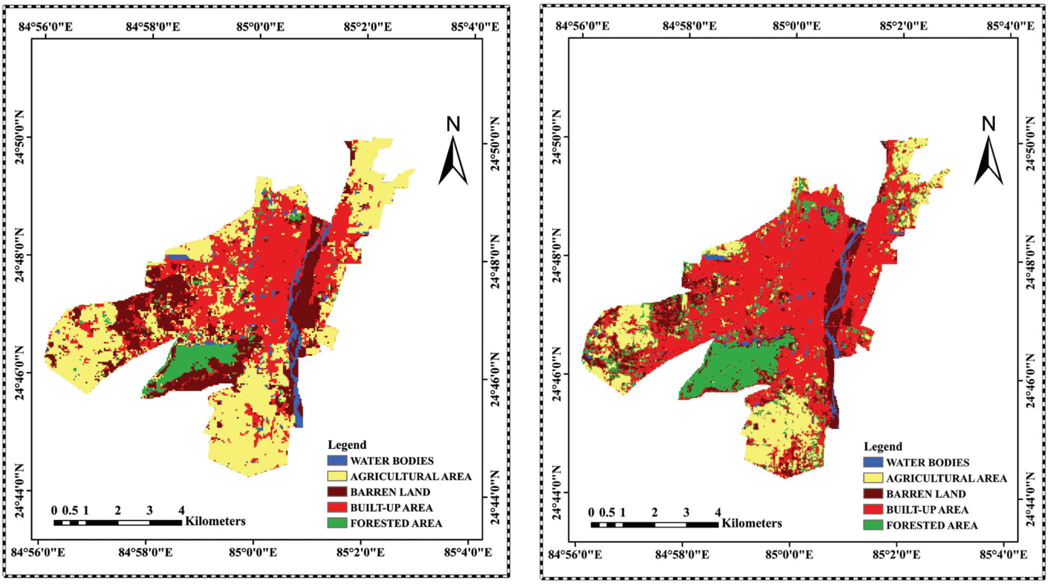

Fig. 3: LULC map for Gaya city. (a) 2000 (b) 2022
Source: Generated through GIS

in horizontal expansion of the Gaya city (City Development Plan, Gaya, 2010). Most of this expansion has taken place at the cost of agricultural land which is easily convertible for non-agricultural purposes. The built-up area was 1543 hectares (32.35%) which increased to 2560 hectares (53.63%) by the year 2022. The increase in built-up area has been 65 percent during the reference period.

Accuracy assessment of classified images

To test the accuracy of the above-classified figures, accuracy assessment becomes an important step for image classification (Foody, 2020). Sometimes due to low spatial and radiometric resolution, objects are misclassified (Rwanga & Ndambuki, 2017). In the accuracy assessment, the random points have been picked up from the classified image and verified from the high-resolution image of Google Earth and ground truth points. Results of the accuracy assessment for classified images for both years are given below in Table 4a and Table 4b.

User's accuracy, Producer's accuracy, and Overall accuracy methods have been applied as the measures of accuracy assessment. The User's accuracy denotes the Commission Error that occurs when a pixel does not belong to the particular class still added to that class. A user's accuracy can be calculated by the number of correctly classified pixels of a particular class divided by the total number of pixels of that class. Producer's accuracy, also known as the Omission error is found in that condition when a pixel that should be added in a particular class is not added in that class. The Producer's accuracy can be calculated by the number of pixels classified accurately divided by the total number of reference pixels of that particular class (Congalton, 1991). The Overall accuracy can be calculated

Table 3: LULC Classes and their Area for the years 2000 and 2022

Classes	2000		2022		Change (2000-2022)	
	Ha	%	Ha	%	Ha	%
Water Bodies	150	3.15	125	2.62	-25	-16.66
Agricultural Land	1908	40.00	810	17.00	-1098	-57.54
Forested Area	255	5.35	694	14.20	+439	+172.15
Barren Land	913	19.15	580	12.20	-333	-36.47
Built-Up Area	1543	32.35	2560	53.63	+1017	+65.91
Total	4769	100	4769	100		

Source: Computed by the authors through attribute tables of classified images

by considering the ratio of the total correctly classified pixels to the total number of pixels (Eq. 3). Kappa's coefficient was obtained (Eq. 4) for the agreement of LULC classification, because sometimes a classified LULC image with a good overall accuracy value may have a poor representation of a particular LULC class (Foody, 2020). All calculations are based on the Error matrix of both classified images, which is also called the Contingency table or Confusion matrix (Skidmore, 1999).

$$Overall\ Accuracy = \frac{Number\ of\ the\ correct\ pixels\ of\ classified\ image}{Total\ numbers\ of\ pixels} \dots\dots(3)$$

$$Kappa\ Coefficient = \frac{(TS \times TCS) - \sum(Total\ Column \times\ Total\ Row)}{TS2 - \sum(Column - Row)} \dots\dots\dots\ ..(4)$$

Where, TS= Total Samples, TCS= Total Correctly Classified Sample

The water bodies and forested areas show the lowest user accuracy of 72 percent for the year 2000 because some water bodies that have been covered with thick aqua vegetation are classified into forested areas automatically, while overall accuracy for the years 2000 and 2022 is 86 percent and 92 percent respectively. This accuracy level shows that it is good image classification. Kappa's coefficient for both reference years is above 0.8 supporting the accuracy of image classification. The higher accuracy of different LULC is attained by changing the Symbology a number of times and by taking the help of Google Earth Pro's historical image during the selection of training samples.

Loss and gain of agricultural land- 2000 and 2022

It is clear from the analysis that agricultural land is the most vulnerable LULC category in terms of area loss. The dark red colour in Fig. 4a shows a huge area being converted to non-agricultural use from agricultural whereas the blue colour shows the area that has been added to agricultural use from other LULC categories during the years 2000 and 2022. Calculation through GIS in the delineated area shows that 1098 hectares (58 percent) of the agricultural area has been lost during this period and has been converted for non-agricultural uses. The loss is calculated after including 99 hectares of area into agricultural land from barren land. This data on agricultural land loss derived through GIS mapping is also being supplemented by the data published by the Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, government of India as given in Table 5. Land use statistics show that the net sown area has declined by more than 14 percent from

1999-2000 to 2020-21 at the district level.

As per Fig. 4b, the maximum loss is shown for agricultural land while the maximum gain is witnessed by the built-up area. A total of 795 hectares (72.40%) of the area lost under agriculture has been devoured by the expansion of the built-up area.

Prediction of LULC for the Year 2030

Based on LULC maps for the years 2000 and 2022, a separate map of LULC has been obtained for the year 2030. This has been done by using IDRISI Selva software. In Fig. 5, it is clearly seen that the agricultural area was nearly wiped off by the expansion of the built-up area.

On the basis of Fig. 5, Table 6 has been derived showing the numeric values under different land use classes for the year 2000 and the predicted year 2030.

As per Fig. 5, the area of water bodies is expected to increase slightly by the year 2030 compared to the year 2000 (+14.66%). The water body area is expected to increase to 172 hectares by the year 2030 largely as the result of better implementation of the water and forest conservation programme launched by the government of Bihar to rebuild and conserve old ponds in the State. The area under the agricultural cover will follow the same trend of declining and is expected to be 657 hectares by 2030. About 65 percent of the agricultural land will vanish by the year 2030 but will decline at a slower rate than before because there will be no such agricultural land left that would be easily converted for non-agricultural uses.

The area of barren land is mainly dependent on the performance of the monsoon which is an uncertain factor (Sangomla, 2022). Due to this reason, the area of barren land does not follow a single trend. It decreased between the years 2000 and 2022 but shows an increase in the predicted image for the year 2030. The forested area follows the same trend of increment in the predicted image and is estimated at 726 hectares by the year 2030 with a total increment of about 184.54 percent from the year 2000. The built-up area

Table 4a: Accuracy values of different LULC classes

Classes	User's accuracy (%)		Producer's accuracy (%)	
	2000	2022	2000	2022
Water Bodies	72	94	100	100
Agricultural Area	98	95	76	84
Forested Area	72	92	78	92
Barren Land	86	88	90	95
built-up area	85	93	100	100

source: computed by the authors from error Matrix

Table 4b: Overall accuracy and Kappa values

	2000	2022
Overall accuracy	86%	92%
Kappa coefficient	0.81	0.90

Source: Computed by the authors from Table-4a, and error matrix

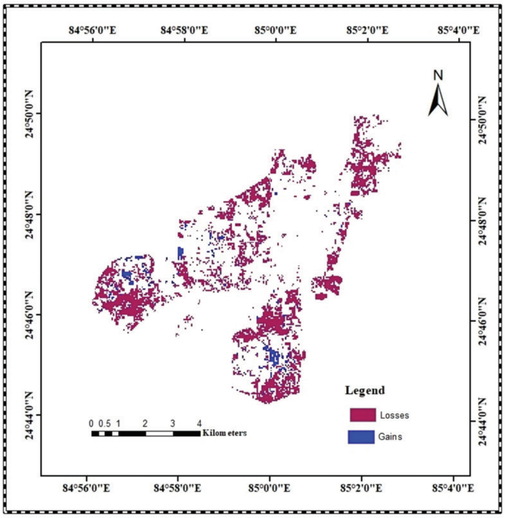

Fig. 4a: Gain and loss in agricultural areas in Gaya city between 2000 and 2022

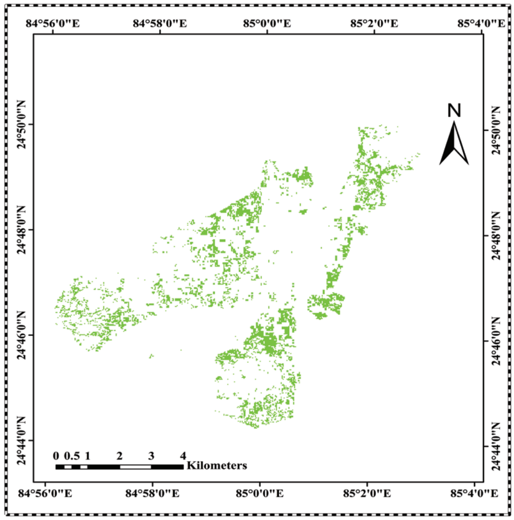

Fig. 4b: Transition of agricultural area to built-up area between 2000 and 2022

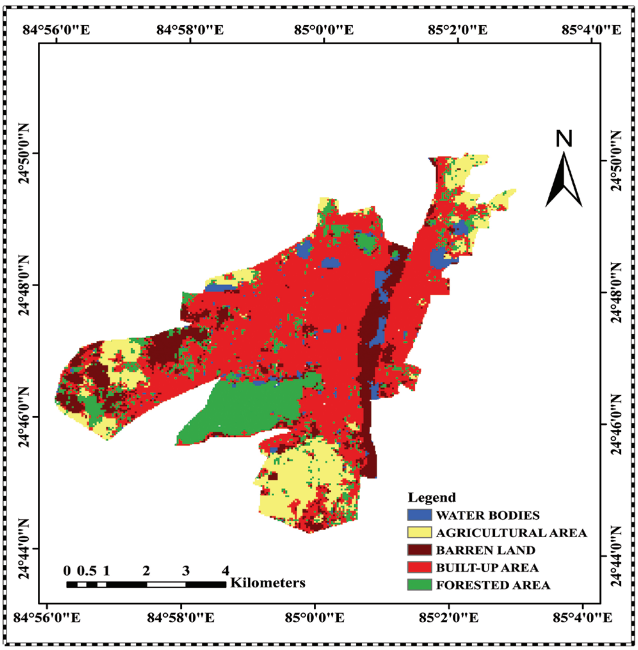

Fig. 5: Predicted LULC map of Gaya City, 2030

Source: Generated through GIS

Table 5: Classification of LULC Categories and Net Sown Area of Gaya District (in Hectares)

Year	Reporting area for LUS	Classification of the reporting area											Net sown area
		Forest	Area under non-agricultural uses	Barren and unculturable land	Total	Permanent pasture and other grazing land	Land Under Misc. use not included in net area sown	Culturable waste	Total	Fallow other than current fallows	Current fallow	Total	
1999-2000	493774	77836	71879	27664	99543	2210	3550	3310	9070	15225	94002	109227	198098
2020-21	493774	77836	73169	27541	100710	2037	3943	3234	9214	30357	105608	135965	170049

Source: NIC, Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, Govt. of India, 2022

Table 6: Predicted changes to LULC, 2030

	Area (in Hectares)		% Change
Classes	2000	2030	2000-2030
Water bodies	150	172	+14.66
Agricultural land	1908	657	-65.56
Barren land	913	634	-30.55
Forested area	255	726	+184.54
Built-up area	1543	2580	+67.20
Total	4769	4769	

Source: Computed by the authors from Table 2 and attribute table of the predicted image

is also going to increase by the year 2030 but much slower than the previous years and is expected to reach 2580 hectares with a total increment of about 66 percent from the base year 2000.

Conclusions and suggestions

The main objective of this paper was to analyse the LULC change between the years 2000 and 2022 for Gaya City in Bihar and to predict a LULC change for the year 2030 in the context of rapidly increasing population and urban expansion. This study tested the LULC change with the help of the Land Change Modeller (LCM) technique and predicted the LULC changes by using the CA Markov Chain Model. The overall accuracy value supplemented with the agreement of Kappa's Coefficient testifies that the images are classified correctly.

It may be concluded that water bodies and barren land are largely controlled by rainfall, while the consistent increase in forests can be attributed to certain government initiatives between the years 2000 and 2022. The spatial distribution of forested areas remained the same over the period but agricultural land has decreased significantly over the period of time.

The agricultural area in Gaya City is declining rapidly because of an increment in the urban population of the city, infrastructure, and residences; the built-up area is expanding and the same trend is likely to continue in the coming decade too as evident from the predicted image. Almost two-thirds of the total agricultural land will be converted into built-up areas by the year 2030. The agricultural land close to the city experiences the twin pressures of housing for the increasing urban population and incessant expansion of supportive infrastructure. These factors are the major causes of the loss of agricultural land around the city. The urban bias of the government policies is evident from these changes in land use making agricultural land more vulnerable to loss (Coulibaly & Li, 2020).

Loss of agricultural land can have disastrous consequences for a city like Gaya as it threatens the food security of its inhabitants largely dependent on urban and peri-urban agriculture (Brahmanand *et al.*, 2013). Because of financial and time constraints, this study was limited to LULC change only and could not address related issues of livelihood and food security of the people.

The government should establish a separate body to assess the loss of agricultural land and its productivity from time to time. As proposed by Firman (2000) and Dekolo *et al.*, (2015), city authorities should regulate the horizontal expansion of the city and take care of urban agriculture seriously whenever some new projects are implemented.

Competing interest

The authors declare that they have no conflict of interest.

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Alok Kumar Dubey*
Research Scholar,
Department of Development Studies,
Central University of South Bihar

Firdaus Fatima Rizvi
Faculty,
Department of Development Studies,
Central University of South Bihar

Akash Tiwari
Research Scholar,
Department of Geography,
Central University of Haryana

*Author for correspondence
E-mail: alokdubey271504@gmail.com