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Quantifying and assessing land use and land cover changes around the critical waterbodies — a case study of Bhagirathi-Hooghly floodplain, East India

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Abstract

The study strictly inclined to the Land Use and Land Cover (LULC) change mapping and assessing, surrounding and inside the abandoned natural river cutoffs and oxbow lakes of Bhagirathi-Hooghly river in the stretch between Katwa and Kalna, East India. Landsat satellite images of selected years (1990, 2000, 2013, and 2020) and supervised classification technique (Maximum Likelihood Classifier) were used for mapping and assessing LULC classification in four selected Areas of Interest, namely A, B, C, and D. Six LULC classes were adopted by deeply observing the selected areas: vegetation, waterbody, sandy land, bare and fallow land, agricultural land, and settlement and built up. LULC matrixes prepared for evaluating the land transformation in three decades (1990–2020). The study results witnessed a huge transformation of land by anthropogenic pressures and river channel migration. In every region, the waterbody area declines and transforms mostly to the fallow land and agricultural land. On the other side, settlement and built-up areas were increased by primarily occupying the agricultural land, bare and fallow land, and vegetation. In the last three decades, a massive expansion happened in agricultural land except region C, primarily for the conversion of bare and fallow land. Except for region B, the conversion of agricultural, bare and fallow, and settlement and built up land to vegetation has triggered the growth of vegetation area. Therefore, the transformation of land, primarily driven by anthropogenic activities, requires utmost concern. The study findings help in proper integrated LULC and resource management, planning, and sustainable development.

Keywords LULC change · Bhagirathi-Hooghly river · Landsat satellite image · Maximum likelihood classifier · LULC change matrix

Introduction

Land use and land cover change detection has been remarkably popularized in the past three decades in land change science for the advancement of remote sensing and computer technology as well as easy and open accessibility of remotely sensed data. However, land use and land cover are used interchangeably in several studies, but these have different meanings (Giri 2012; Lillesand et al. 2015). Land use refers to the human activity and economic activities

on a piece of land (Ardli and Wolff 2008; Comber 2008; Lillesand et al. 2015). On the other hand, the land cover is a physical feature observable in the earth's surface (Giri 2012; Lillesand et al. 2015). Human activities predominantly alter land use and land cover of the earth's surface, and when the changes are combined globally, they greatly trigger the functions of the earth system (Lambin et al. 2001; Lambin and Geist 2006). Various human-induced activities like demographic changes (migration, population growth), globalization, technological development, and human responses to the changing economic condition are the primary driving forces for land use and land cover change (Lambin and Geist 2006).

LULC change study has been accomplished with the comparison in between the present and historical data, which is obtained by remote sensing techniques and by using the integrated approach of remote sensing and GIS; the data is interpreted accurately, which let us be aware of the trends and patterns of land changes, amounts of land changes, and associated challenging issues (Loveland et al.

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2016; Nath et al. 2018). Moreover, LULC change studies try to unfold some queries such as (1) Where is the land use and land cover change emerging? (2) What type of land use and landcover classes are changing? (3) What type of changes taking place? (4) What are the rates and degrees of change? (5) What are the controlling factors and causes of land use and land cover change (Loveland et al. 2016).

LULC changes have been accelerated in the earth's surface over the last 30 years (Lambin and Geist 2006), and also enormous studies have been done. Similarly, numerous studies have been accomplished on LULC change surrounding waterbodies like lakes, rivers, wetlands. In the USA, LULC change mainly happened due to the increase in new construction (40%) and decrease in agricultural land (2.3%) and forest land (2.3%), including wetland area (38%) in the watershed of the Great lake from 1992 to 2001 (Wolter et al. 2006). In China, Lake Qinghai has encountered extreme declination in respect of water level (6.7 cm a-1) and area (6.4 km² a-1) between 1959 and 2007 (Li et al. 2008). Karki et al. (2018) have shown that an acute reduction has been observed in the forest area and lake area of Lake Inle in Myanmar but cropland and seasonal freshwater areas have increased in 25 years. Settlements, cultivated land, grasslands, water, and bare soil area have been increased, and forest land cover and wetlands area has been decreased heavily in Lukanga lake catchment of Zambia from 1997 to 2017 (Changwe 2020). Bhattacharjee et al. (2021) conclude cropland, bare soil, and shallow water have been increased in the Northeastern wetland ecosystem, Bangladesh, resulting in reduced deep-water body and vegetation. Besides, natural vegetation areas decreased, and residential and commercial areas increased surrounding Bolgoda wetland of Srilanka from 2000 to 2019 (Athapaththu et al. 2020). Amin et al. (2014) have revealed the land transformation, and anthropogenic activities in Dal lake (India) converted the freshwater lake into a deteriorated pond. Similarly, the Wular lake of India drastically transformed because of decreasing lake area (−62.5%) and marshy land (−94.117%) and increasing settlements (642.85%) (Mushtaq and Pandey 2013). Large-scale haphazard development, agricultural expansion around the pong dam, and excessive siltation in the lake affected the Pong dam of Himachal Pradesh (Malik and Rai 2019). From the information regarding LULC of an area, we can understand the relationship between forest, agricultural land, wetland, and settlement, including river morphology which supports bridging the gaps of knowledge (Kotoky et al. 2012).

Several difficulties and transformations have been observed in the earth surface due to the LULC change, which is unsystematic development, deteriorating wetland condition, degradation of soil and water quality, destruction of biodiversity and ecosystem, including global and regional climate change (Anderson et al. 1976; Chase et al. 1999; Houghton 1999; Pimm and Raven 2000; Ellis et al. 2010; Foley et al. 2005). Globally, 35 years (1982–2016) of study of Song et al. (2018) reveals tropical deforestation and agricultural extension, temperate reforestation or afforestation, farmland intensification, and urbanization all show regional dominance in land-use change. Moreover, land-use changes increase mean surface warming of 0.27 °C per century (Kalnay and Cai 2003). Dewan et al. (2021) observed that the urban expansion and less presence of vegetation in the cities of Bangladesh increase urban warming. In Alberta, Canada, changing patterns in LULC triggers the change in albedo which exceptionally alter the local environment (Hassan et al. 2021). In Beressa watershed of the Blue Nile basin, Yohannes et al. (2021) observed that Hydrological Ecosystem Services has been highly degraded by farmland and plantation. The water availability of upper catchment in the Bagmati river is significantly changed due to the shortage of regional annual rainfall and increasing urbanization (Tuladhar et al. 2019). Rahman et al. (2021) found that rising population and rapid urbanization negatively affect the waterbodies and agricultural land and also increase the flood susceptibility in Sunamganj, Bangladesh. Hence, the LULC change detection and its several impact assessment studies play a vital role in different parts of the world for proper planning, policy framing, and systematic development, which ensure environmental sustainability and improvement.

In my study area, the Bhagirathi-Hooghly river bank experienced a fast-increasing population density for rapid acceleration of birth rate and large-scale migration (Rudra 2018). Moreover, massive urbanization and agricultural expansion continuously change the LULC scenarios of the bank of the Bhagirathi-Hooghly river. Hence, these frequent anthropogenic activities create enormous pressure on the river and adjacent abundant cutoffs and oxbow lakes. Also, The Bhagirathi-Hooghly river migrates its channel frequently in its vulnerable stretches (Rudra 2018). Thus, extreme settlement displacement, losses of human lives, livestock, and crops have occurred due to the random meandering and excessive channel migration (Bag et al. 2019). Additionally, the floods in the study area causes huge settlement displacement (Chatterjee and Mistri 2013) as most of the floodplain area occupied by the migrated people from East Pakistan (Presently Bangladesh) after partition (Rudra 2020). Therefore, LULC changes along the bank of the Bhagirathi-Hooghly river and surrounding and inside the oxbow lakes require utmost concern. That is why four major oxbow lakes and plenty of abundant decaying cutoff have been selected in the stretch between Katwa and Kalna of Bhagirathi-Hooghly river to study the LULC change and land transformation over three decades (1990 to 2020). No scientific study has been found on LULC change and land transformation in the selected study area. However, the area has been encountered by continuous and haphazard transformation anthropogenically as well as naturally. In the present-day context, there is an urgent need for this study for sustainable LULC model framing, including systematic micro-level planning and policymaking. Therefore, the study's primary contribution is to quantify and evaluate the LULC changes over three decades (1990–2020) surrounding and inside the oxbow lakes and abandoned meanders along the bank of

Table 1 Information about analyzed satellite imageries

Satellite	Sensor	Spatial resolution	Spectral bands used	Wavelength (µm)	Path/row	Acquisition date
Landsat 5	TM	30 m	1–4	0.45–0.90	138/44	30.01.1990
Landsat 7	ETM +	30 m	1–4	0.45–0.90	138/44	17.11.2000
Landsat 8	Oli	30 m	2–5	0.45–0.88	138/44	15.12.2013, 02.12.2020

Bhagirathi-Hooghly river in the stretch between Katwa and Kalna. In addition, another focus of the study is to assess land transformations of Area of Interest (AoI) from 1990 to 2020.

Study area

The study was conducted in the floodplain areas along the Bhagirathi-Hooghly river. Bhagirathi-Hooghly river is the western distributary of river Ganga, which flows more than 500 km in West Bengal. The lower 280 km stretch of the river is under tidal regime, named as Hooghly river (Rudra 2018). This study was carried out in the floodplain areas of the tidal portion and the non-tidal portion of the river, which deeply focused on the diversity of water bodies. Four rectangular Areas of Interest (AoI) were taken by considering the 2020 Landsat satellite image along the Bhagirathi-Hooghly river, namely A, B, C, and D. The mentioned areas were very important for study as these areas were fulfilled with abundant natural resources. Three major oxbow lakes, plenty of meandering cutoffs, natural ponds, natural vegetation have tremendously faced the pressure of excessive growth in population density and infiltration. The Bhagirathi-Hooghly river is dynamic in this region, and shifting its channel frequently, causes massive LULC changes. Also, anthropogenic activities like cropland extension, settlement, and built up area increase were severe and uncontrolled. Hence, many abundant river channels and oxbow lakes were lost their previous glory by becoming fallow land and then agricultural land or settlement and built up area. That is why the study is mostly focused on natural waterbodies along the river from Katwa to Kalna. Two districts were located in the selected Areas of Interest, namely East Barddhaman and Nadia. The area is under quaternary sedimentary deposits as well as lowest and highest elevation of the area is −83 m and 41 m, respectively (Wandrey and Law 1997).

Materials and methodology

Database

The entire study is dependent on secondary source of database. Two types of secondary data were required: satellite data and ancillary data. For assessing the land use and land cover changes in the study area, Landsat satellite images have been collected from 1990 to 2020. Almost cloud-free (< 1%) day time Landsat satellite imageries were freely acquired from USGS Earth Explorer online archive. All acquired imageries were registered in the UTM/WGS 1984 projected coordinate system. Landsat TM, ETM +, and Oli sensors imageries have been chosen to carry out the LULC classifications and only Visible (Blue, Green, Red Bands) and Near Infrared (NIR) bands were used to prepare composite images. Other information regarding collected and used satellite imageries are described in Table 1. Side by side, ancillary data as a form of Google Earth Pro images for three decades (1990–2020) were required for validation and verification of the accuracy of the classified images.

Table 2 Class details of Land Use and Land Cover classification

Class	Allocated Symbol	Descriptions
Vegetation	V	Sparse forest vegetation, vegetation of the waterbodies, fruit cultivation (like banana and mango), and other vegetation
Waterbody	W	Rivers, ponds, oxbow lakes, and abandoned cutoffs of the river
Sandy land	SL	Riparian open sandy areas, sandy char lands, and other uncultivated sandy areas, sandy areas around brick kilns
Agricultural land	AL	Croplands, horticultural lands used for vegetables and flowers cultivation, and pastures
Bare and fallow land	BFL	Riparian sediment deposits, open playground, transitional areas around the water body, land with or without shrub, and brushes which is likely to be changed in near future
Settlement and built up	SBU	Residential and industrial areas, educational institute and commercial complexes, railway and roadway networks, bridges, brick kilns, green houses of agriculture, and other human-made open concrete structures

LULC classification

Classification scheme

The classification scheme of six (6) classes has been adopted by extensive Google Earth observations and validated that with rigorous field visits following Anderson et al. 1976. Also, the color, tone, pattern, and texture of the Landsat images have played an important role in the selection of six (6) classes. LULC classes have been computed for the years 1990, 2000, 2013, and 2020. The classes were Vegetation, Water Body, Sandy Land, Bare and Fallow Land, Agricultural land, Settlement, and Built Up. It has been confirmed that each class sufficiently represented the selected Areas of Interest by avoiding possible overlaps and exclusions as far as possible. The explicit information regarding each and every class has been described in Table 2.

Data preprocessing

Image preprocessing of every Landsat image from 1990 to 2020 has been accomplished, including radiometric correction, compositing different spectral bands and masking, and clipping areas of interest. Four masked and then clipped images have been adopted as an Areas of Interest (AoI) from 1990, 2000, 2013, and 2020 to compare and change detection.

Image classification

Classification of the image leads to the extraction of classes of information from multispectral images. Image classification in remote sensing can be accomplished using supervised, unsupervised, and object-based image classification (Vivekananda et al. 2021). In the supervised classification technique, numerical descriptors of several classes have been specified to the computer algorithms to categorize pixels (Lillesand et al. 2015). In the past few years, supervised classification has been recognized as the important and effective method for automatically generating LULC classification of extended geographical areas (Bruzzone and Prieto 2001; Richards and Jia 2006). Generally, prior knowledge about the study region is essential for supervised classification, as it requires ground-truth data for validation of each classified class (Kim 2016). Maximum Likelihood Classification (MLC) has been chosen for this study among the several well-known supervised classifications. MLC is a tool which is one of the most popular and common in remote sensing for image analysis (Bolstad and Lillesand 1991; Richards and Jia 2006), and also, it is extensively used in the moderate-resolution satellite image (Strahler 1980; Bayarsaikan et al. 2009; Vivekananda et al. 2021). The maximum Likelihood decision rule quantitatively assesses the variance and covariance of the pattern of the spectral responses for classifying an unknown pixel (Lillesand et al. 2015). Moreover, it depends on probability for assigning pixels in a particular class (Moreno and Larriva 2012).

In this study, the MLC method has been executed using the Arc GIS 10.3 software which includes several steps. Firstly, training sample selection has been made for each of the four Areas of Interest for selected years (1990, 2000, 2013, 2020) in the selected stretch of Bhagirathi-Hooghly River by carefully verifying the satellite images with Google Earth Pro software. Region D and Region C consist of maximum (170.71 km^2) and minimum (59.94 km^2). As the Areas of Interest are some smaller critical pockets in the lower part of the Great Plain of India, more than 50 training samples were assigned for the class with extensive areal coverage (like, Agricultural Land) and less than 50 training samples for the class with smaller areal coverage (Like, Sandy Land). Then, training samples were merged for producing six classes. Then, a total of sixteen (16) signature files (.sig) were created for the LULC change study of three decades (1990–2020). Lastly, sixteen LULC maps have been prepared using those signature files before accuracy assessment.

Accuracy assessment by classification error matrix

"A classification is not complete until its accuracy is assessed" (Lillesand et al. 2015). Hence, after producing all LULC maps, the accuracy assessment of all classified images for selected years has been attained using the Arc GIS 10.3 software. Error matrix or Confusion matrix is the most common method for assessing accuracy. Also, it helps us to understand the relationship between known reference data and corresponding outcomes of automated LULC classification (Lillesand et al. 2015).

For Accuracy assessment, a few steps were followed. In the beginning, stratified random sampling was adopted for getting sample points to ensure the adequate representation of comparatively smaller classes. Here, the class of every image was a stratum, and then random sampling was carried out in each class to generate an ideal result. Secondly, the sample points were converted into a KML file (.kml) using the conversion tool of the Arc GIS 10.3 for importing it in the Google Earth Pro. After that, each sample point has been verified and validated with the ground-truth data of Google Earth and then tabulated the outcome manually in the attribute table of the respective classified image. Finally, the error matrix and kappa coefficient were produced for calculating the accuracy of the classified image. As per Lillesand et al. (2015), the error matrix for accuracy assessment and the kappa coefficient ($\widehat{k}$) has been generated.

Generally, the value of kappa coefficient ($\widehat{k}$) ranges between 0 and 1, where the value equals 1 represents true or perfect agreement between reference data and automated classifier; and less than 1 represents less perfect agreement (Lillesand et al. 2015; Hua and Ping 2018). Several scholars have a different view on the kappa coefficient. After reviewing several pieces of literature, it can be said more precisely that less than 0.4 is considered as poor and very poor agreement, values lie in 0.4 to 0.55 are considered as fair agreement, values from 0.55 to 0.7 are noted as the good agreement, values 0.7 to 0.85 exhibit

Table 3 Land Percentage in Region A, B, C, and D from 1990 to 2020

Class	Region A				Region B				Region C				Region D			
	1990	2000	2013	2020	1990	2000	2013	2020	1990	2000	2013	2020	1990	2000	2013	2020
	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)	Area (%)
V	17.23	17.09	22.89	19.06	17.12	23.96	18.14	15.87	9.43	13.69	25.77	20.28	12.96	33.54	21.39	17.36
W	6.73	10.46	6.18	5.4	7.67	12.28	9	6.11	10.65	12.15	8.1	6.79	7.34	10.42	7.79	6.69
SL	6.23	3.64	1.04	2.73	3	3.08	4.57	4.51	4.88	7.63	3.56	3.21	5.6	3.76	2.52	2.78
AL	29.61	35.41	38.87	51.48	40.12	25.49	37.4	45.22	44.37	24.6	29.82	40.21	36.88	22.34	40.22	43.73
BFL	28.45	17.7	15.85	4.76	21.12	19.94	20.74	16.19	19.01	26.74	19.37	17.67	25.24	15.46	16.99	8.02
SBU	11.75	15.7	15.17	16.57	10.97	15.25	10.14	12.09	11.65	15.19	13.38	11.83	11.98	14.49	11.09	21.43

V, vegetation; *W*, waterbody; *SL*, sandy land; *AL*, agricultural land; *BFL*, bare and fallow land; *SBU*, settlement and built up

Table 4 Changing patterns of LULC from 1990 to 2020 in A, B, C, and D regions

Class	Region A				Region B				Region C				Region D			
	1990–2000	2000–2013	2013–2020	1990–2020	1990–2000	2000–2013	2013–2020	1990–2020	1990–2000	2000–2013	2013–2020	1990–2020	1990–2000	2000–2013	2013–2020	1990–2020
	Change (%)	Change (%)	Change (%)	Net change (%)	Change (%)	Change (%)	Change (%)	Net change (%)	Change (%)	Change (%)	Change (%)	Net Change (%)	Change (%)	Change (%)	Change (%)	Net change (%)
V	−0.14	5.8	−3.83	1.83	6.84	−5.82	−2.27	−1.25	4.26	12.08	−5.5	10.85	20.57	−12.15	−4.03	4.4
W	3.72	−4.28	−0.78	−1.33	4.61	−3.28	−2.89	−1.56	1.49	−4.05	−1.31	−3.86	3.08	−2.63	−1.1	−0.65
SL	−2.59	−2.6	1.68	−3.5	0.08	1.49	−0.07	1.51	2.74	−4.07	−0.34	−1.67	−1.84	−1.24	0.26	−2.82
AL	5.81	3.45	12.61	21.87	−14.63	11.91	7.82	5.1	−19.77	5.22	10.39	−4.16	−14.53	17.88	3.5	6.85
BFL	−10.75	−1.85	−11.09	−23.69	−1.18	0.8	−4.55	−4.92	7.72	−7.37	−1.69	−1.34	−9.78	1.53	−8.96	−17.21
SBU	3.95	−0.53	1.4	4.82	4.28	−5.1	1.95	1.12	3.54	−1.81	−1.55	0.18	2.5	−3.39	10.33	9.44

V, vegetation; *W*, waterbody; *SL*, sandy land; *AL*, agricultural land; *BFL*, bare and fallow land; *SBU*, settlement and built up

very good agreement, and values more than 0.85 represent an excellent agreement among the images (Hua and Ping 2018).

LULC change detection and land transformation

Remote sensing data has the major advantage of capturing and recording significant spatial–temporal information, and it has been widely used for change detection in recent decades (Lu et al. 2004; Lillesand et al. 2015). Change detection is the most common digital image analysis technique and is denoted as the identification and characterization of changes of remote sensing images over a period of time (Lillesand et al. 2015). Several techniques of change detection have been developed, and the most common techniques are image differencing post-classification comparison matrix and Principle Component Analysis (PCA) (Lu et al. 2004; Mishra et al. 2020). A post-classification comparison matrix was generated of classified images from 1990 to 2000, 2000 to 2013, 2013 to 2020, and finally 1990 to 2020 by using the Arc GIS 10.3 and MS-Excel 2016 software for evaluating aggregate changes in the study area. After that, in 1990 and 2020, both the years have been selected for showing land transformation over three decades in the selected areas.

Result

Status of LULC from 1990 to 2020

Over three decades, the LULC status of different selected years (1990, 2000, 2013, 2020) has been assessed in selected four regions (A, B, C, D) along the bank of the Bhagirathi-Hooghly river, West Bengal. D (173.77 km^2) is the Largest, and C (59.94 km^2) is the smallest in the selected regions. Multiband satellite images of Landsat have been used. The images were classified and evaluated in six classes: vegetation, waterbody, sandy land, agricultural land, bare and fallow land, and settlement and built up.

LULC of 1990

Results of LULC 1990 of A region have shown that the most prominent land share (29.61%) has been occupied by agricultural land, followed by bare and fallow land (28.45%) (Table 3).

Vegetation and settlement and built up areas were covered by 17.23% and 11.25%, respectively, while waterbody and sandy land secured the smallest share of land of 6.23%. In the case of B region, vegetation and settlement and built up area covered by 17.12% and 10.97%, respectively, whereas sandy land (3%) and agricultural land (40.12) consisted of smallest share and largest share, respectively (Table 3). In addition, 7.67% and 21.12% share of land covered by waterbody and Bare and fallow land, respectively. In region C, 9.43% and 10.65% of the land were covered by vegetation and waterbody, respectively, while dominated LULC class in that region is agricultural land (44.37%) followed by bare and fallow land (19.01%) (Table 3). Consequently, settlement and built up occupied 11.65% of the land, and the least occupied LULC class is sandy land (4.88%) in region C. LULC Result from the region D reveals that the majority of the land is occupied by agricultural land (36.88%), followed by bare and fallow land (25.24%). In comparison, sandy land (5.6%) and waterbody (7.34%) both the class secured the least share (Table 3). Settlement and built up covered 11.98% area as well as vegetation-covered 12.96% of the area. From the overall scenario, it is observed that in all regions, majority of land share has been occupied by Agricultural land followed by bare and fallow land while least share of land is under sandy land.

LULC of 2000

In region A, the result tabulated in Table 3 indicated different LULC classes had occupied the area, viz. vegetation-covered 17.09%, waterbody covered around 10.46%, agricultural land and bare and fallow land covered maximum area of 35.41% and 17.70%, respectively. In contrast, sandy land covered a minimum area of 3.64%; additionally, 15.70% area has been occupied by settlement and built up. In 2000; waterbody, agricultural land, settlement, and built up were increased, and others were declined from 1990. In the B region, the largest area has been occupied by agricultural land (25.49%) and vegetation (23.96%), while waterbody covered 12.38%. Despite that, bare and fallow land secured 19.94%, and the smallest area of 3.08% has been occupied by sandy land. Also, 15.25% of the area was covered by the settlement and built up. A prominent increase has been observed in settlement and built up, vegetation, and waterbody from the previous year. Moreover, agricultural land faced a massive decrease of around 15% (Table 4). In the case of the C region,

Table 5 Overall accuracy and Kappa Coefficient of 2013 and 2020

Region	2013		2020	
	Kappa coefficient	Overall accuracy	Kappa coefficient	Overall accuracy
A	0.8496	87.54%	0.8709	89.24%
B	0.8972	91.55%	0.8895	90.83%
C	0.8739	89.58%	0.9323	94.41%
D	0.9002	91.72%	0.7761	81.35%

Table 6 LULC change matrix in between 1990 and 2020 in Region A and B

	Class	Region A Area in km² (2020)							Region B Area in km² (2020)						
		AL	BFL	SL	SBU	V	W	Total	AL	BFL	SL	SBU	V	W	Total
Area in km² (1990)	AL	**26.9***	0.9	0.96	5.63	7.93	0.83	43.14	**15.61***	3.23	0.8	1.77	3.21	0.79	25.42
	BFL	22.01	**3.22***	1.32	6.47	6.69	1.74	41.46	6.27	**3.3***	1.03	0.8	1.62	0.36	13.38
	SL	3.54	0.92	**0.44***	1.4	2.32	0.45	9.08	0.58	0.43	**0.22***	0.07	0.14	0.45	1.9
	SBU	4.14	0.77	0.21	**7.09***	4.79	0.13	17.13	1.81	0.97	0.17	**2.48***	1.34	0.17	6.95
	V	16.38	0.38	0.37	3.02	**4.6***	0.36	25.11	3.07	1.14	0.18	2.53	**3.58***	0.35	10.85
	W	2.05	0.76	0.67	0.54	1.43	**4.37***	9.81	1.3	1.18	0.45	0.01	0.16	**1.75***	4.86
	Total	75.02	6.94	3.97	24.15	27.77	7.87	145.73	28.65	10.26	2.86	7.66	10.05	3.87	63.35

AL, agricultural land; *BFL*, bare and fallow land; *SL*, sandy land; *SBU*, settlement and built up; *V*, vegetation; *W*, waterbody; * unchanged land

settlement and built up and bare and fallow lands were witnessed a striking increase to 15.19% and 26.74%, respectively (Table 3). Also, vegetation, waterbody, and sandy land were exhibited a slight increase to 13.69%, 12.15%, and 7.63%, respectively, while a large-scale (around 20%) decrease has been observed in only agricultural land (Table 4). The result of region D indicated an exceptional increase of about 20% in vegetation (Table 4), and its land share is 33.54% (Table 3). Sandy land, agricultural land, and bare and fallow land decreased to 3.76%, 22.34%, and 15.46%, respectively, while waterbody and settlement and built up encountered by little increase to 10.42% and 14.49%, respectively (Table 3). In the year 2000, overall sandy land is secured least covered area, and agricultural land is mostly covered class except for region C and D. In region C, bare and fallow land and in region D, vegetation occupied majority of the area.

LULC of 2013

For A region, a dominated share occupied by agricultural land of about 38.87%, which is a result of the increase in the land share of around 3% (Table 4). On the other side, sandy land became very minimum to 1.04%. Vegetation increased to 22.89%, while

bare and fallow land, waterbody, settlement, and built up collectively lost its land share (Table 3). In the B region, the result of classification revealed several increments and decline, viz. agricultural land increased to 37.40%. It is the prime class while bare and fallow land increases to 20.74%, sandy land increases to 4.57%, and contrary to these, settlement and built up, vegetation, and waterbody decreased to 10.14%, 18.14%, and 9%, respectively. In cases of C region, vegetation and agricultural land have faced increment, and declining nature has been observed in four classes: bare and fallow land, settlement and built up, vegetation, and waterbody (Table 4). Moreover, the most and least dominant class is agricultural land (29.87%) and sandy land (3.56%), respectively. In the D region, the maximum percentage of area occupied by agricultural land (40.22%) followed by vegetation (21.39%), while sandy land and waterbody have decreased and secured the least share of the area, which were 2.52% and 7.79%, respectively. In addition, settlement and built up have decreased to 11.09%, whether bare and fallow land slightly increased to 16.99%. The overall scenario depicted that the agricultural land holds most of the land share, and the least share has been occupied by sandy land.

Table 7 LULC change matrix in between 1990 and 2020 in Region C and D

	Class	Region C Area in km² (2020)							Region D Area in km² (2020)						
		AL	BFL	SL	SBU	V	W	Total	AL	BFL	SL	SBU	V	W	Total
Area in km² (1990)	AL	**15.03***	3.38	0.69	2.01	4.42	1.08	26.6	**39.31***	3.28	1.04	9.71	8.26	1.35	62.95
	BFL	4.61	**3.7***	0.27	0.71	1.62	0.5	11.4	21.3	**4.29***	0.96	7.62	7.12	1.78	43.08
	SL	1.27	0.44	**0.33***	0.14	0.38	0.37	2.93	4.42	0.47	**0.83***	1.42	1.11	1.3	9.56
	SBU	1.77	1.04	0.11	**2.36***	1.45	0.27	6.99	5.43	1.06	0.1	**9.1***	4.58	0.2	20.46
	V	0.29	0.23	0.01	1.86	**3.24***	0.02	5.65	2.97	2.37	0.05	8.43	**8.03***	0.27	22.13
	W	1.14	1.8	0.53	0.02	1.04	**1.85***	6.39	1.7	1.98	1.64	0.48	0.46	**6.27***	12.53
	Total	24.1	10.59	1.93	7.09	12.15	4.07	59.94	75.13	13.45	4.62	36.76	29.56	11.18	170.71

AL, agricultural land; *BFL*, bare and fallow land; *SL*, sandy land; *SBU*, settlement and built up; *V*, vegetation; *W*, waterbody; * unchanged land

LULC of 2020

In A region, agricultural land tremendously increased and covered more than half of the total land (Table 3). Moreover, settlement and built up and sandy land increased to 16.57% and 2.73%, respectively. Despite these, bare and fallow land, vegetation, and waterbody collectively lost their land share (Table 3). In the B region, the lion's share (45.22%) of land has been occupied by agricultural land, increasing by almost 8% from 2013 (Table 4). Settlement and built up area also increased to 12.09%. On the other hand, bare and fallow land, vegetation, waterbody, and sandy land have been decreased to 16.19%, 15.87%, 6.11%, and 4.51%, respectively. The result of LULC in the C region indicated that the largest share of land had been occupied by agricultural land (40.21%), and it is the only class that increased from 2013 (Table 3). The other five classes, viz. settlement and built up, vegetation, sandy land, bare and fallow land, and waterbody, were decreased to 11.83%, 20.28%, 3.21%, 17.67%, and 6.79%, respectively. In cases of D region, agricultural land and settlement and built up both have increased to 43.73% and 21.43%, respectively, by which both the classes have secured maximum coverage of land share. Settlement and built up also gain a remarkable percentage of land of 21.43%,

as well as a slight increase, has been found in sandy land. Bare and fallow land, waterbody, and vegetation decreased to 8.02%, 6.69%, and 17.36%, respectively. In 2020, it was observed that agricultural land gained a remarkable land share in every region which makes it the most dominant class.

Accuracy assessment

Accuracy assessment of classified LULC maps was carried out for the year of 2013 and 2020. The accuracy assessment of 1990 and 2000 could not be performed due to the low-resolution Google Earth images. In the time of accuracy assessment, several misclassifications were noticed in between ground truth data and classified images, such as riparian unexposed bedrock sometimes classified as the Settlement and built up, riverside sandy land as the agricultural land and settlement and built up as the bare land. Additionally, settlement and built up sometimes considered as the vegetation and waterbody as bare and fallow land because of the juxtaposition in some patches of each region. Moreover, bare and fallow land is sometimes classified as waterbody because of the misclassification in the transitional fallow land zone surrounding the waterbody.
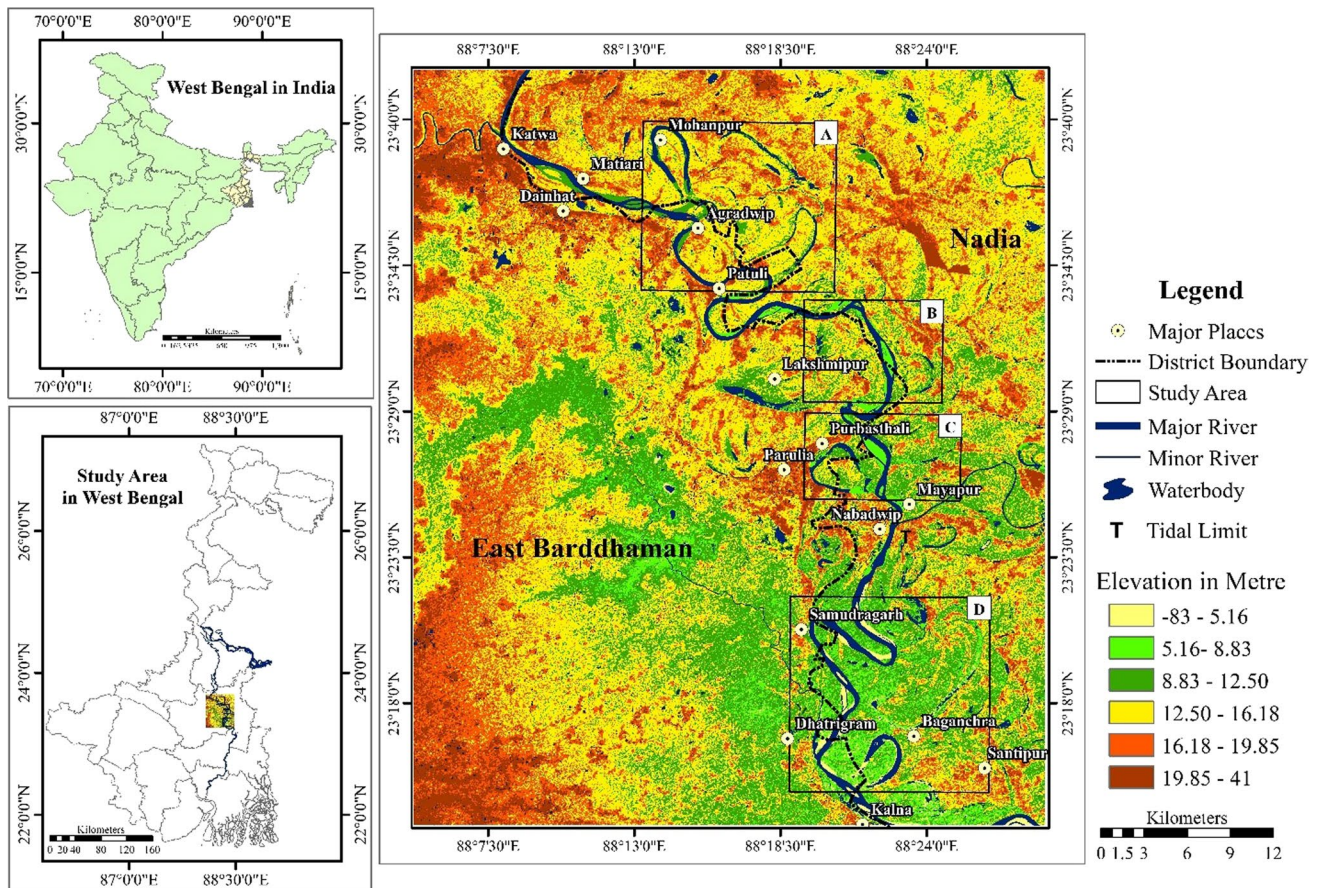

Fig. 1 Location map of the study area

The most used reliable Kappa Coefficient method has been used for accuracy assessment (Okeke and Karnieli 2006). Table 5 shows all the details of overall accuracy and kappa coefficient of 2013 and 2020. In 2013, the overall accuracy of classified images of regions A, B, C, and D were 87.54%, 91.55%, 89.58%, and 91.72%, respectively. Additionally, the kappa value of region A, B, C, and D were 0.8496, 0.8972, 0.8739, and 0.9002, respectively. The kappa value of regions B, C, and D indicates excellent agreement, and the value of region A indicates very good agreement among the images. In 2020, the results indicated that the overall accuracy of classified images of regions A, B, C, and D were 89.24%, 90.83%, 94.41%, and 81.35%, respectively. In Addition, the Kappa Coefficient of A, B, C, and D regions were 0.8709, 0.8895, 0.9124, and 0.8226, respectively. The kappa value of classified images of regions A, B, and C were denoted as excellent agreement and region D as very good agreement.

Overall scenarios of changing patterns of LULC

Table 6 and 7 show the changes in LULC and the present LULC status of the changed land. The bold letter is recognized as the unchanged land in the tables. Conversion Over three decades (1990–2020) has been measured and evaluated. A significant trend of conversion has been observed in every region, which was conversion happened from waterbody to fallow land, in the primary stage, and then those fallow land converted to agricultural land.

Changing LULC patterns in between 1990 and 2020 in Region A

From 1990 to 2020, primary changes were noticed in bare and fallow land to agricultural land from region A. As per Table 6, About 22.01 km^2 bare and fallow land converted to agricultural land as the gradual increase in population density as well as agricultural practices. It was observed that bare and fallow land was converted all over the region. Moreover, 16.38 km^2 of vegetation has been converted to agricultural land due to the reasons mentioned above, and it was the second-largest conversion of region A. 7.93 km^2 of agricultural land was converted to vegetation due to the expansion of social forestry, agroforestry, mango, and guava cultivation in different parts of the region. Also, a second major conversion of 5.63 km^2 has been found in agricultural land to settlement and built up along the riverside due to the excessive and haphazard migration of the river channel, resulting from human-made settlement and built-up

Fig. 2 Flow chart showing methodology of the study
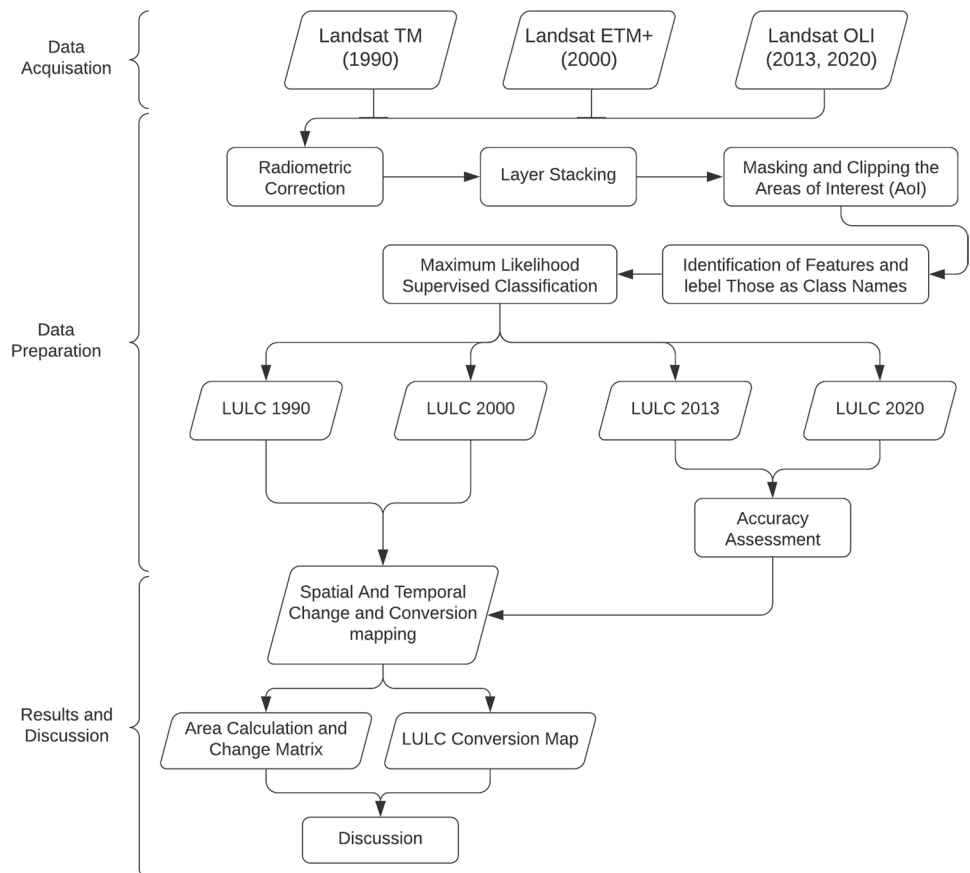
area shifting. Most of the sandy land (3.54 km²) was converted to agricultural land as the agricultural dominance took place in a riverine sandy area and char lands of the region. Around 5.25 km² settlement and built up area turned into agricultural land, bare and fallow land, sandy land, and waterbody because of the massive channel shifting and continuous flooding of river Bhagirathi-Hooghly. The majority of the conversion occurred in the riparian floodplain area of the river. In addition, 4.79 km² settlement and built up area converted to the vegetation in different settlement patches as a result of social forestry, reforestation programs. It was observed that the waterbody was gradually decreased over three decades and 4.37 km² of waterbody remained unchanged (Table 6). The waterbody became agricultural land, settlement and built up area, sandy land, vegetation, and bare and fallow land due to the annihilation of abandoned river meander, cutoff, oxbow lakes, and natural ponds. Also, sediment deposition in the convex bank of the river

accelerated land gains by which the waterbody turned into several other LULC classes. The most prevalent LULC class is agricultural land, and the least prevalent is sandy land in that region.

Changing LULC patterns in between 1990 and 2020 in Region B

In the B region, Table 6 shows that 15.61 km² of agricultural land remains unchanged, and it was the largest in that particular area. Around 3.23 km² of agricultural land was converted to bare and fallow land due to the expansion of the width of the river channel and mid-channel bar formation in the river. Moreover, 3.21 km² of agricultural land was changed to vegetation as the fruit cultivation (like mango, litchi, guava, papaya) increased, and agroforestry was expanding over the decades. The most remarkable transformation of 6.27 km² has been observed from bare and fallow land to agricultural land due to the rising population and
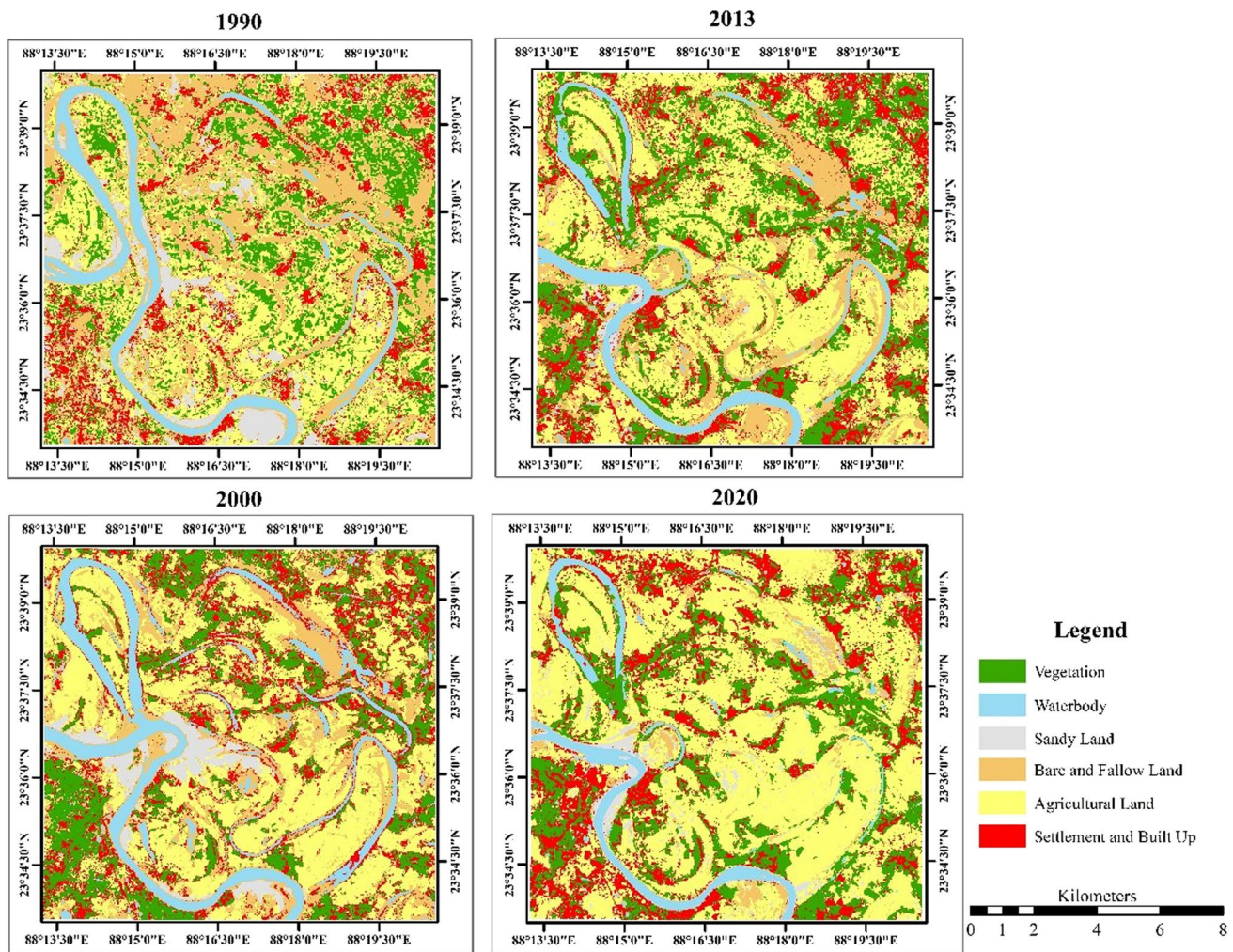

Fig. 3 LULC map of selected years of Region A

excessive food requirements over three decades. The bare and fallow land turned into sandy land, and vice versa along the Bhagirathi-Hooghly river as a result of point bar and mid-channel bar formation due to the erosional and depositional work carried out by the river Bhagirathi-Hooghly. Though sandy land is very marginal, it has a significant role in the riparian system; near about 1 km^2 sandy land converted to agricultural land and fallow land due to the rapid agricultural expansion and increasing sediment deposition in the convex bend as well as mid-channel bar of the river while 45 km^2 of the sandy land converted to the waterbody due to the mid-channel bar formation in Bhagirathi-Hooghly river which accelerated erosional activity in the sandy land of the concave bank near Rukunpur. The settlement and built up area encountered a slight increase over three decades, near about 0.5 km^2. Maximum conversion in settlement and built up was observed from settlement and built up to agricultural land, which was 1.81 km^2; this is due to the devastating flood in the floodplain area of the river Bhagirathi-Hooghly in 2000. It was observed that agricultural land played a dominant role all over the region in three decades and 3.07 km^2

vegetation area also converted to the agricultural land all over the part due to deforestation and agricultural expansion while 2.53 km^2 of vegetation changed to settlement and built up, which was mostly happened within the oxbow lakes and left bank of the river. Considering the waterbody, almost 1 km^2 of waterbody decreased over three decades, and the majority of the waterbody was encountered by agricultural expansion.

Changing LULC patterns in between 1990 and 2020 in Region C

The most considerable amount of 4.61 km^2 of bare and fallow land was converted to agricultural land, and the reason was the same as cited previously for other regions (Table 7). Contrary to this, 3.38 km^2 of agricultural land degraded to the bare and fallow land, and it mainly was occurred along the oxbow lakes and rivers due to the frequent flooding.

The second-largest conversion was 4.42 km^2, and it happened from agricultural land to vegetation as a result of shifting from traditional grain-based farming to fruit cultivation
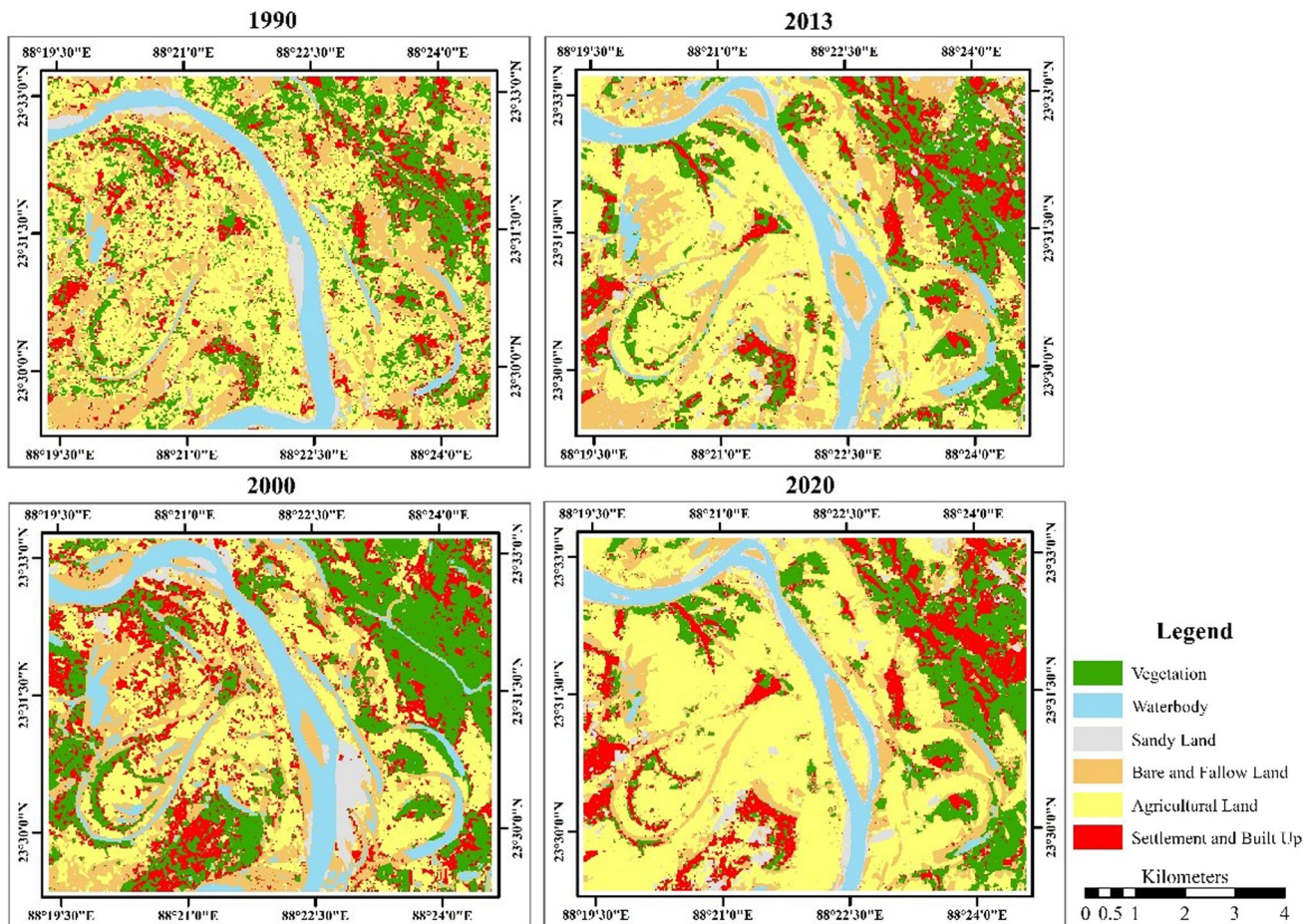

Fig. 4 LULC map of selected years of Region B

and agroforestry. On the other hand, only 0.29 km² of land converted from vegetation to agricultural land. In cases of sandy land, it was observed that most of the sandy land (1.27 km²) was converted to agricultural land in the sandy riparian area due to the rapid agricultural expansion. In the past three decades, 1.77 km² settlement and built up changed to agricultural land, while 2.01 km² of agricultural land converted to the settlement and built up because of rapid expansion of rural areas like Purbasthali, Bhandartikuri, and Mayapur. Also, 1.45 km² settlement and built up turned into vegetation, and contrary to this, 1.86 km² vegetation area converted to the settlement and built up, and the reason behind these was mentioned above in the description of previous regions. Ultimately, the area of settlement and built up is increased over three decades. Waterbody is the most important in this region as it consists of two major oxbow lakes and rivers. From 1990 to 2020, almost 3 km² waterbody converted to the bare and fallow land and agricultural land (Table 7). It is due to the farmland expansion on newly formed char land and rapid declination of oxbow lakes.

Changing LULC patterns in between 1990 and 2020 in Region D

In Region D, from 1990 to 2020, agricultural land held the largest share (39.31 km²) of unchanged land due to the agricultural predominance from the 1990s (Table 7). The majority of the

agricultural land (9.71 km²) changed to settlement and built up as a result of growing population and expansion of urban and rural areas like Kalna, Santipur, Bhaluka, Samudragarh, Nasratpur, and Dhatrigram, while only 5.43 km² settlement and built up area was changed to agricultural land because of repetitive migration of residents due to the destructive floods happened almost in every year in low-lying areas. Moreover, 8.26 km² of agricultural land was converted to vegetation due to the expansion of agroforestry, reforestation, and cultivation of mango, guava, jujube, papaya, litchi, etc., mainly in the south-eastern part of the region. On the other side, 2.97 km² vegetation area converted to the agricultural land due to the deforestation and agricultural stretching in mid-channel bar near Krishnadebpur, inside oxbow lake near Kalna and different settlement patches located all over the region. Bare and fallow land has been reduced abruptly over three decades, and maximum (21.30 km²) of it converted to agricultural land while only 3.28 km² agricultural land degraded to the bare and fallow land. Around 7.12 km² bare and fallow land has converted to vegetation due to social forestry, afforestation program which was primarily occurred in the left bank of the river Bhagirathi-Hooghly. Contrary to this, 2.37 km² of vegetation has also changed to bare and fallow land mostly along the river meanders and abandoned cutoffs as a result of evolving river course. In addition, a large amount (7.62 km²) of bare and fallow land has also changed in settlement and built up area in the last three decades due to the expansion of several urban and rural areas such as Samudra Garh, Kalna,
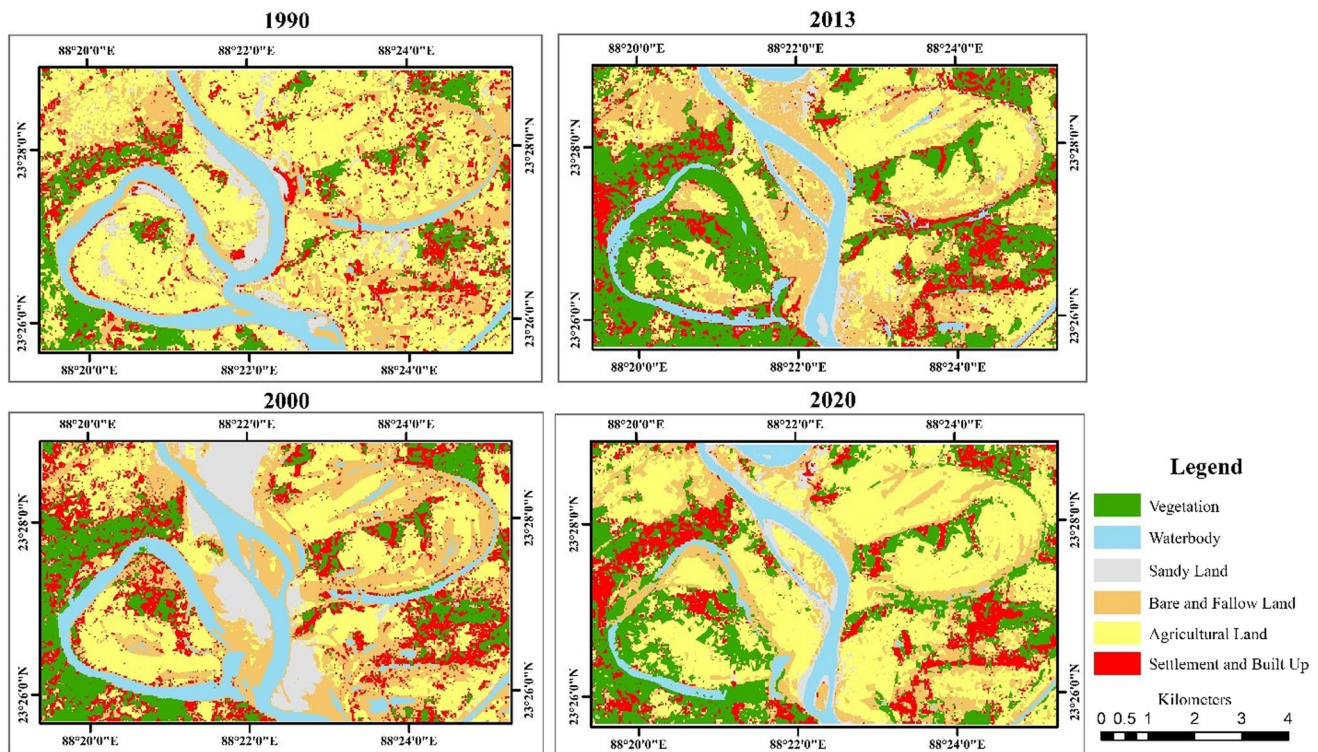

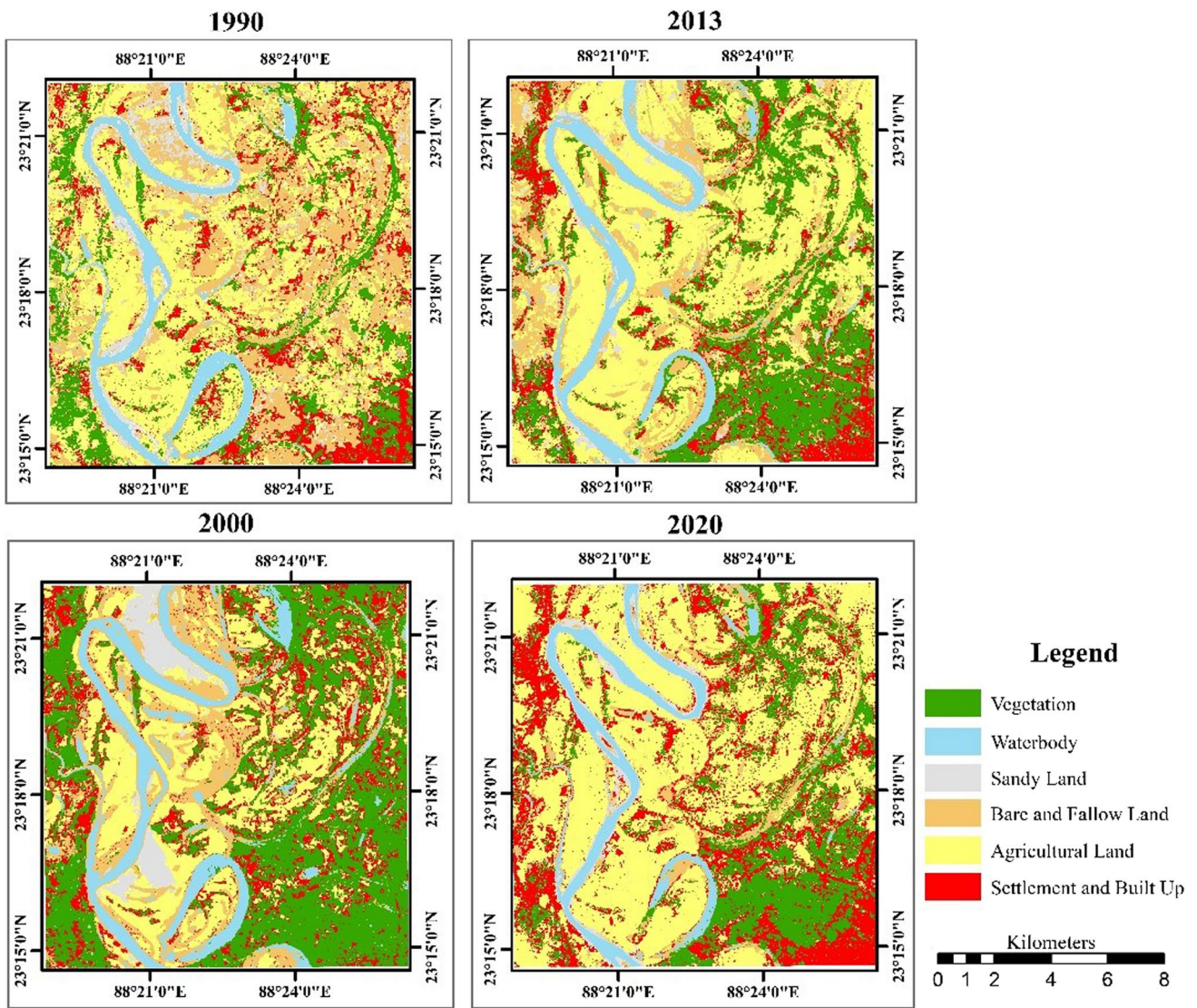**Fig. 5** LULC map of selected years of Region C

Fig. 6 LULC maps of selected years of Region D

Dignagar, Baganchra, and Santipur. The sandy land was significantly reduced, and most of the reduced land was converted into agricultural land (4.42 km^2) along both rivers (Table 7). In the south-eastern part of the region, 4.58 km^2 settlement and

Table 8 Overall change scenarios in A, B, C and D Regions

Class	1990–2020							
	Region A		Region B		Region C		Region D	
	Change in area	Change in %	Change in area	Change in %	Change in area	Change in %	Change in area	Change in %
Vegetation	2.67	1.83	− 0.79	− 1.25	6.50	10.85	8.03	4.40
Waterbody	− 1.94	− 1.33	− 0.99	− 1.56	− 2.31	− 3.86	− 0.91	− 0.65
Sandy land	− 5.11	− 3.50	0.95	1.51	− 1.00	− 1.67	− 4.73	− 2.82
Agricultural land	31.88	21.87	3.23	5.10	− 2.49	− 4.16	13.02	6.85
Bare and fallow land	− 34.52	− 23.69	− 3.12	− 4.92	− 0.80	− 1.34	− 29.14	− 17.21
Settlement and built up	7.02	4.82	0.71	1.12	0.11	0.18	16.77	9.44

built up area has changed to vegetation while 8.43 km² vegetation became a settlement and built up area due to expansion of urban and rural areas. Considering the waterbody, in the last three decades more than 1 km² of waterbody was decreased, and bare and fallow land, agricultural land and sandy land expansion is the main reason behind declination of waterbody. Unscientific usage, massive exploitation, and improper planning were accelerating the waterbody's changes from bare and fallow land to agricultural land (Figs. 1, 2, 3, 4, 5, and 6).

Overall changing scenario

The overall changes in all regions (A, B, C, and D) from 1990 to 2020 have been depicted in Table 8. Regarding region A, it was observed that maximum change has occurred in agricultural land and bare and fallow land, where agricultural land changed positively and bare and fallow land changed negatively. In total, 31.88 km² of land became agricultural land, denoted a 21.87% increase, whether bare and fallow land decreased by 34.52 km². The most significant

increase found in agricultural land and the reduction in bare and fallow land were seen in the A region. The B and C region is tiny compared to the A and D, and changes in LULC is very marginal in these regions. Among B and C regions, maximum positive change has been observed in vegetation in the C region, which is 10.85%. Contrary to this, top negative change (− 4.92%) has been found in bare and fallow land. In the D region, change in bare and fallow land and settlement and built up was prominent. Among these, settlement and built up changed and increased by 16.77 km² (9.44%) while bare and fallow land decreased by 29.14 km² (17.21%) (Figs. 7, 8, 9, and 10).

Discussion and conclusion

Prior work has documented the LULC change detection and prediction in different critical parts of the world and its role in environmental degradation (like vegetation loss, waterbody degradation). However, these studies have either
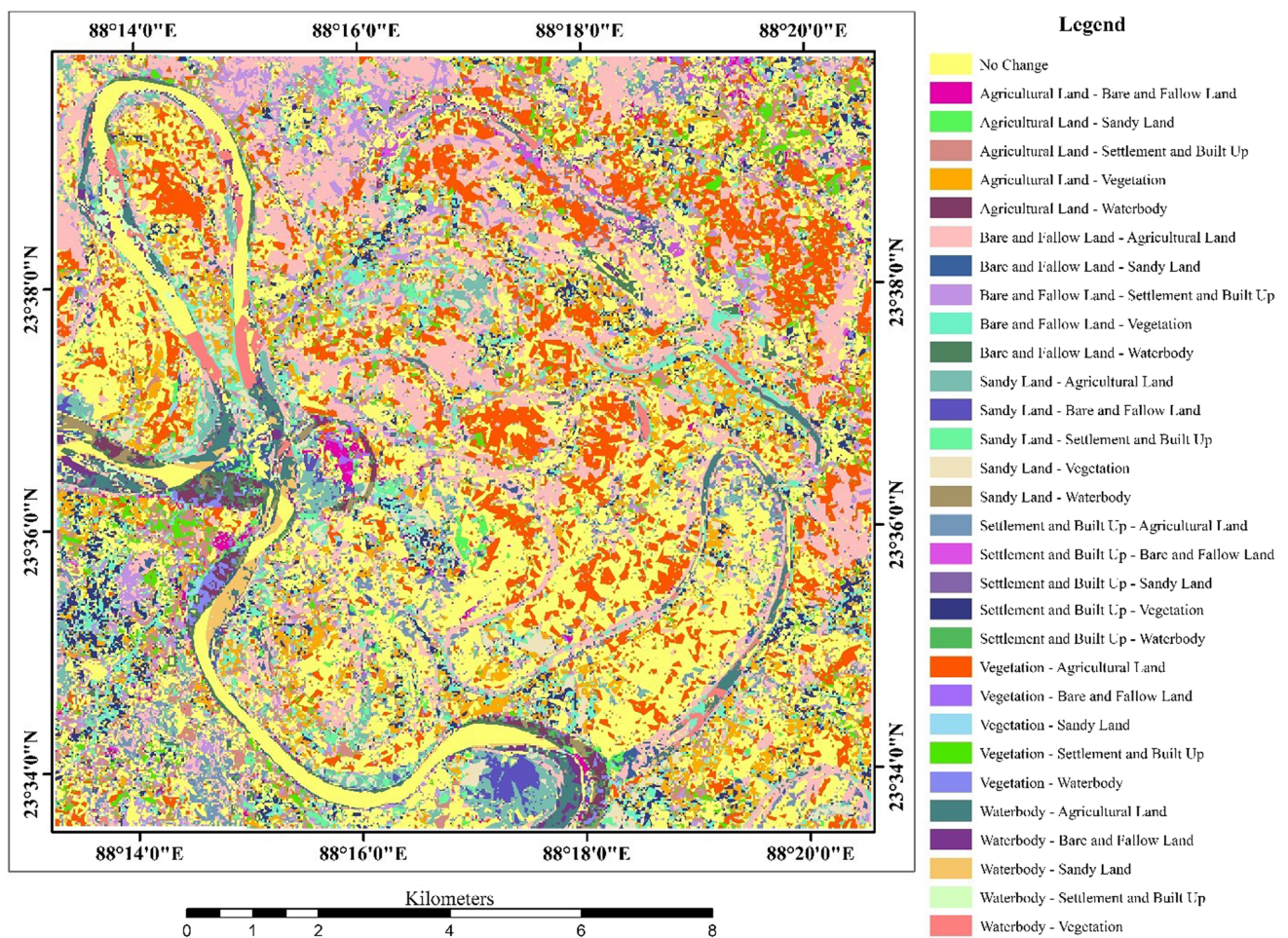

Fig. 7 LULC conversion map for Region A since 1990–2020

been very primitive or have not focused on the particular study area. The previous researches in the selected study area had concentrated on changing channel dynamics (Islam and Guchhait 2017) and its socio-economic impacts on the riparian communities (Islam and Guchhait 2015), changing channel morphometry (Bag et al. 2019), issues related to wetlands (Chatterjee et al. 2021), changing LULC patterns in Bhagirathi floodplain (Misra and Roy 2019). However, in this study, we quantify and evaluate the LULC changes and assess land transformations over three decades (1990–2020) surrounding and inside the oxbow lakes and abandoned meanders, lying in the lower part of the Great Plain of India, along the bank of Bhagirathi-Hooghly river in the stretch between Katwa and Kalna. A total of four rectangular areas (A, B, C, and D) have been chosen by focusing the critical water bodies, including river channel, four major oxbow lakes and plenty of abundant cutoffs to show the rise and fall of LULC classes. In accordance with the previous findings, overall, we found that the LULC changes in the selected areas were driven mainly by anthropogenic activities (Alam et al. 2019; Liu et al. 2020), especially by the expansion in agricultural land (Sánchez-Cuervo et al.

2020) and settlement and built up areas (Alam et al. 2019; Chamling and Bera 2020).

Our study provides surprising observation that the LULC of selected areas were frequently changed in the last three decades, and waterbody, sandy land, bare and fallow land exhibit a negative change in most regions (Table 8, . 11) Waterbody declined by -1.33%, -1.56%, -3.86%, and -0.65% in Region A, B, C, and D, respectively. From the entire scenario of LULC, it was revealed that waterbodies, especially abandoned natural river cutoffs and oxbow lakes, were decreased over three decades by the extreme expansion of agricultural land and settlement and built up areas in all regions. The study finding is consistent with other observations (Zhang et al. 2017; Ganaie et al. 2020; Bhattacharjee et al. 2021; Jamal and Ahmad 2020); however, it contradicts with Mishra et al. (2020) finding where waterbody was increased in the Rani Khola watershed, Sikkim, and in the Bhutan-Bengal foothill region, waterbody also increased due to the artificial pond construction and spill channel formation (Chamling and Bera 2020). In many cases, it has been observed that agricultural practice is taking place in the bed of abandoned cutoffs and
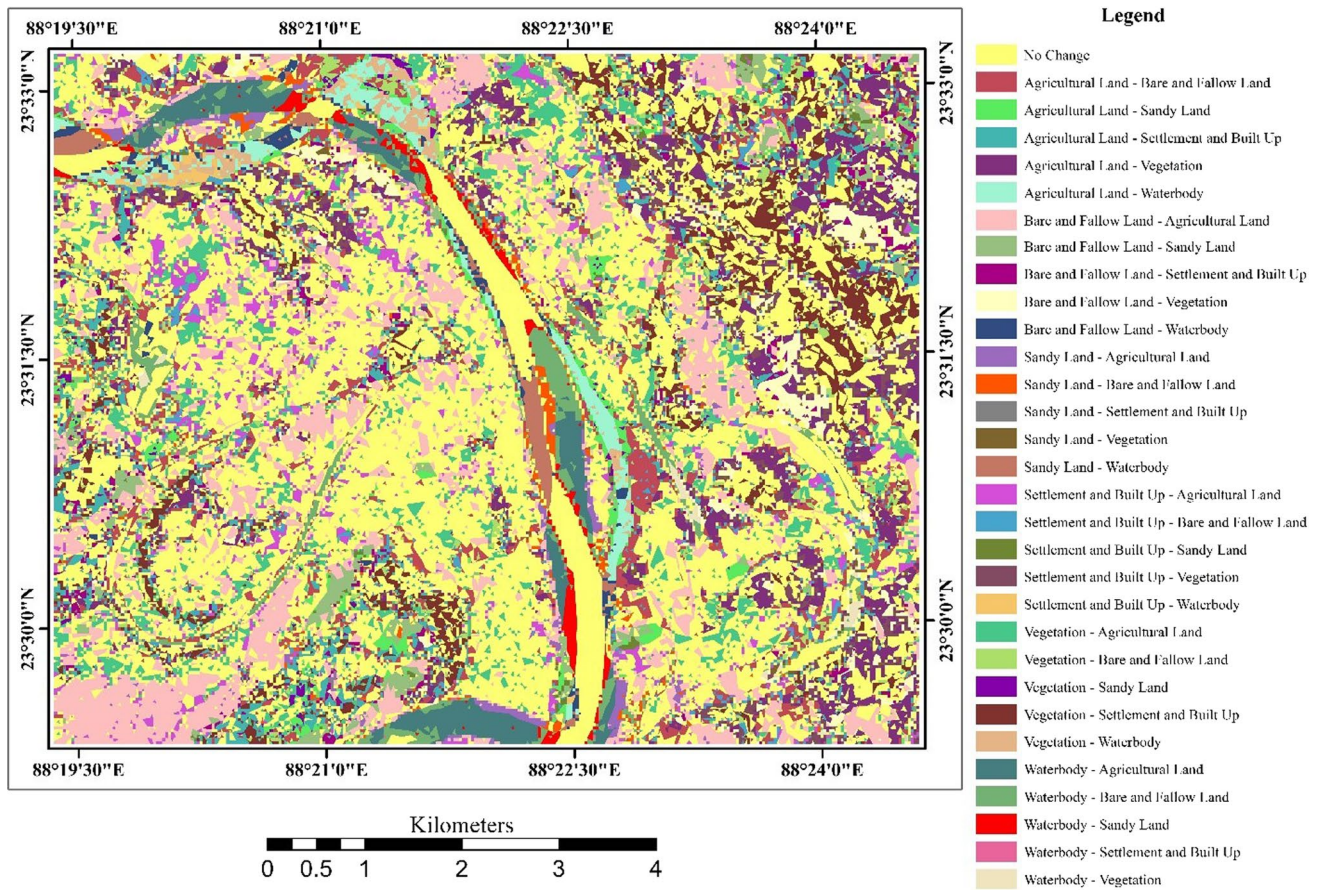

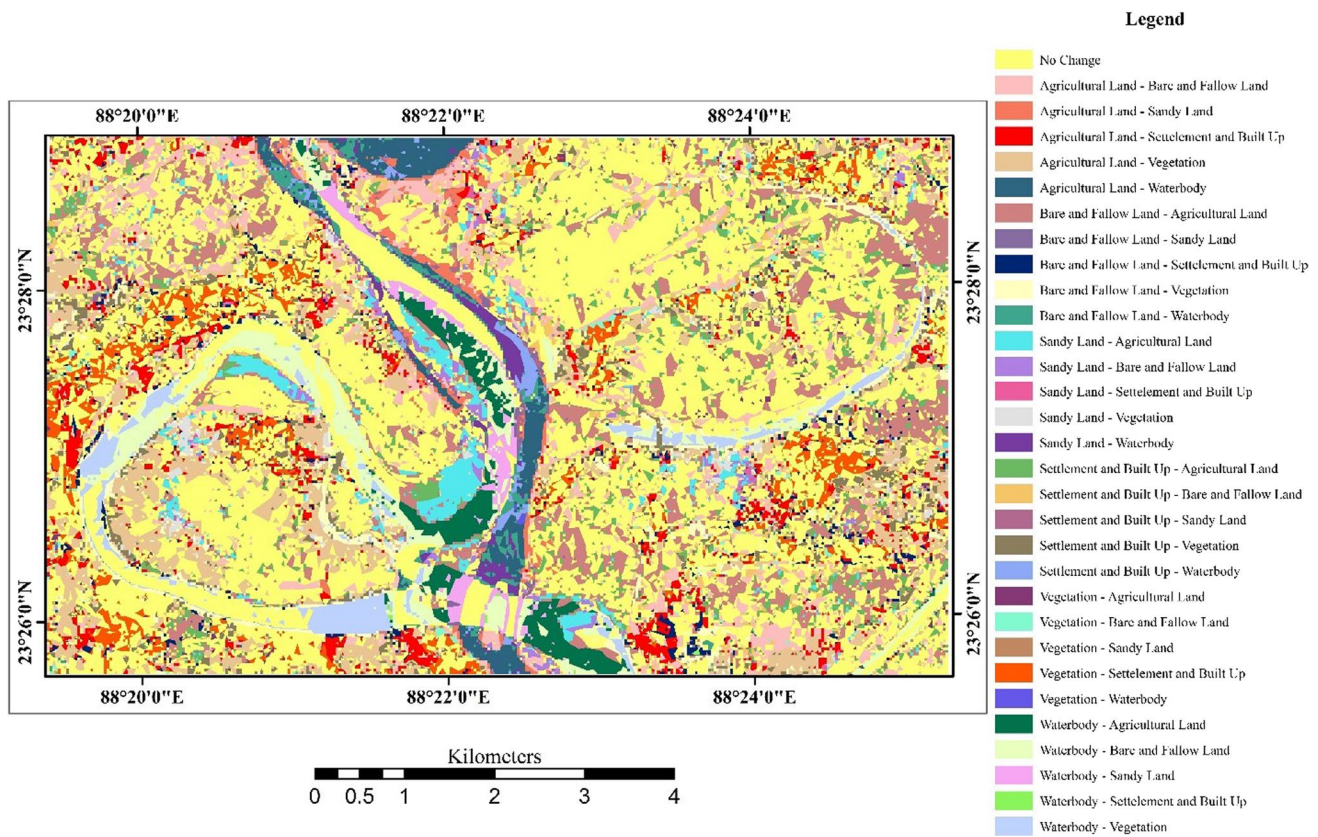**Fig. 8** LULC conversion map for Region B since 1990–2020

Legend

- No Change
- Agricultural Land - Bare and Fallow Land
- Agricultural Land - Sandy Land
- Agricultural Land - Settlement and Built Up
- Agricultural Land - Vegetation
- Agricultural Land - Waterbody
- Bare and Fallow Land - Agricultural Land
- Bare and Fallow Land - Sandy Land
- Bare and Fallow Land - Settlement and Built Up
- Bare and Fallow Land - Vegetation
- Bare and Fallow Land - Waterbody
- Sandy Land - Agricultural Land
- Sandy Land - Bare and Fallow Land
- Sandy Land - Settlement and Built Up
- Sandy Land - Vegetation
- Sandy Land - Waterbody
- Settlement and Built Up - Agricultural Land
- Settlement and Built Up - Bare and Fallow Land
- Settlement and Built Up - Sandy Land
- Settlement and Built Up - Vegetation
- Settlement and Built Up - Waterbody
- Vegetation - Agricultural Land
- Vegetation - Bare and Fallow Land
- Vegetation - Sandy Land
- Vegetation - Settlement and Built Up
- Vegetation - Waterbody
- Waterbody - Agricultural Land
- Waterbody - Bare and Fallow Land
- Waterbody - Sandy Land
- Waterbody - Settlement and Built Up
- Waterbody - Vegetation

Fig. 9 LULC conversion map for Region C since 1990–2020

oxbow lakes. Also, unplanned built up (Like brick kilns, roads) continuously and unprecedently shapes the water-bodies. Waterbody was a tremendous natural resource, and it helps to maintain balance in the hydrological cycle (Li et al. 2018), groundwater replenishment (Arya et al. 2020), and several anthropogenic activities. Therefore, loss in the areal coverage of waterbody could lead to extreme lopsidedness in the environment and humankind shortly. Another triggering factor of LULC change in the particular study area is frequent and haphazard flooding, which primarily happened due to the dam-included discharge and excessive rainfall in Jharkhand (Rudra 2020). In my study time period (1990–2020), several years (1998, 1999, 2000, 2003, 2006, 2015) were affected by small or devastated floods and which causes abrupt LULC changes in the floodplain area. Additionally, a striking decrement in the area of bare and fallow land has also been observed, which were − 23.69%, − 4.92%, − 1.34%, and − 17.21% for regions A, B, C, and D, respectively. Mostly, bare and fallow land was replaced by agricultural land and faced a massive declination in each area from 1990 to 2020. In contrast with the previous finding, Wu et al. 2013 has shown an incredible increase in bare and fallow land and

decrease in agricultural land in Hangzhou metropolitan area, China, and Pilgrim et al. (2014) also revealed that the bare ground experienced a positive change in the Lake Issaqueena watershed, South Carolina. In contrast, several study findings (Malik and Rai 2019; Mawenda et al. 2020; Mishra et al. 2020) align with the present finding. Moreover, Sandy land, facing declination of − 3.50%, − 1.67%, and − 2.82% in Region A, C, and D, respectively, transformed most of the sandy land in agricultural land. Contrary to this, Rimal et al. (2017) has noticed that sandy area has been increased by predominantly converting the waterbody. On the other hand, Horqin sandy land in inner Mongolia has been declined, whereas irrigated agricultural land and salinized area increased (Bai et al. 2017).

In contrast, agricultural land, settlement and built up, and vegetation overall faced positive change in three decades (Table 8; Fig. 11). Agricultural land was the prevalent class in this particular region as the area was located in the lower stretch of the Great Plain of India, and it was flourished by agriculture from the primitive period. It was facing remarkable growth in A, B, and D regions by predominantly reducing the bare and fallow land. In the past three decades, rapid growth in population density has increased food demand and
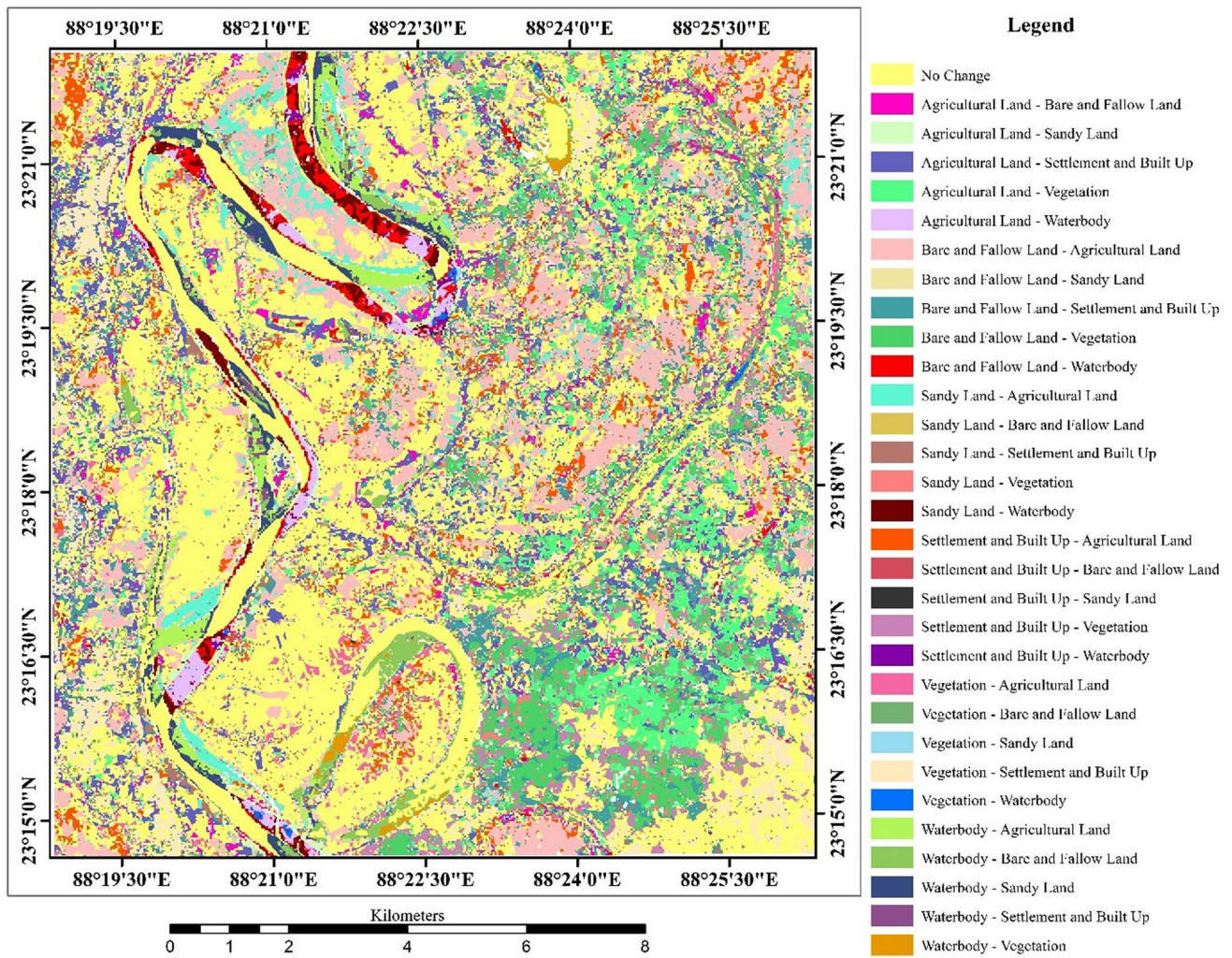
Fig. 10 LULC conversion map for Region D since 1990–2020

strikingly accelerated agricultural expansion. This finding has similarities with other works in the Wami river Basin, Tanzania (Twisa and Buchroithner 2019) and Pong dam, India (Malik and Rai 2019). The expansion in agricultural land has been found in the A, B, and D region, representing

massive changes of 21.87%, 5.10%, and 6.85%, respectively. Additionally, settlement and built up areas were facing the growth of 4.82%, 1.12%, 0.18%, and 9.44%, respectively, and It increased in all regions, proving the increasing population and expansion of rural and urban areas. Several

Fig. 11 Diagrammatic representation of overall changes (%) in all regions
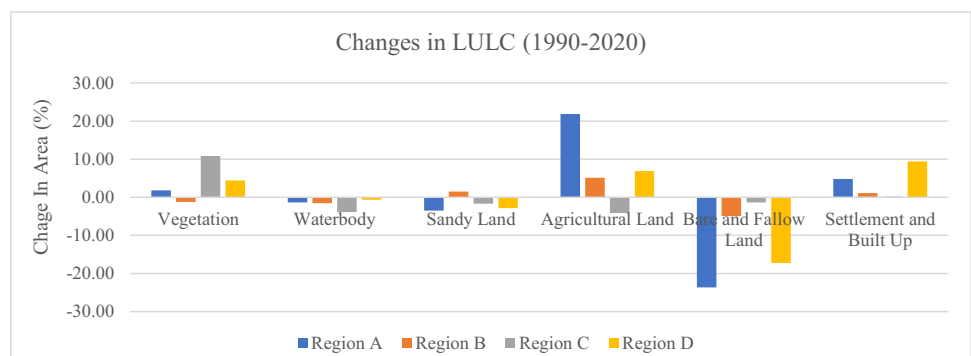
studies (Miheretu and Yimer 2017; Alam et al. 2019; Chamling and Bera 2020; Ganaie et al. 2020) have shown similar tendencies. Primarily, the reason behind the areal expansion of settlement and built up was the conversion of agricultural land, bare and fallow land, and vegetation. Except for region B, vegetation was increased in all regions by 1.83%, 10.85%, and 4.40% in A, C, and D, respectively. The agricultural land was predominantly replaced by vegetation, and it was due to the expansion of social forestry, riverside tree plantation for riverbank protection, reforestation, agroforestry, and expansion of fruit cultivation like mango, banana, guava, and papaya. Also, in Sikkim, the dense forest has been increased due to the afforestation program sustainable agroforestry program (Mishra et al. 2020). However, different studies (Ganaie et al. 2020; Naikoo et al. 2020; Nath et al. 2021) have observed declining vegetation.

Over three decades, the most dominant LULC class in all regions was agricultural land. It significantly increased in every part except region C. At the same time, the least dominant class was sandy land as its land share in all areas were significantly less as well as it was decreased from 1990 in every region except region B. Waterbody was declining over three decades in all areas and needed utmost concern to save waterbodies. The detailed and thorough observations on waterbody revealed that abandoned cutoffs and oxbow lakes of river Bhagirathi- Hooghly, natural and artificial ponds, and the river itself declined over three decades due to several deleterious anthropogenic activities (like unplanned settlement and built up construction, conversion of waterbody into fallow land and agricultural land, increasing water usages for rising population). Vegetation has slightly increased except for region B. In addition, settlement and built-up increased in all regions, put a remarkable footprint in every class, and changed the scenarios of each region.

Chatterjee et al. (2021) showed land transformation and land reclamation through LULC change for two specific wetlands in the selected study area. Moreover, Misra and Roy (2019) focused on changing the pattern of LULC in the Bhagirathi floodplain. The inefficiency of comprehensive and substantial research work in LULC change and transformation assessment in the selected critical Areas of Interest have made some of our study findings completely new. The evaluation of the transformation of selected Land Use and Land Cover (Figs. 7–10) in the selected study area over three decades is, to our knowledge, the first of its kind.

The study provides compelling evidence to identify the crucial areas and the affected LULC classes. By identifying those classes, some hotspot areas can be demarcated for giving special attention and proper planning. Great attention is required on waterbody as it was severely declined over the periods. As the population in the study area is increasing rapidly, agricultural area and settlement and built up area expansion has occurred. Hence, there is an extreme need to control the haphazard expansion by formulating and applying practical, sustainable, comprehensive land-use policies. Our study also enriched local people, policymakers, researchers, scholars, and administrators by providing substantial shreds of evidence of abrupt and unplanned changes in some critical pockets in the lower stretch of the Great Plain of India. The overall study evaluation and findings are essential for ensuring sustainable LULC practices and sound policymaking.

Declarations

Conflict of interest The authors declare no competing interests.

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