Object-Based Classification to Evaluate LULC Changes and Socio-Economic Mobility with Google Earth Engine: A Case Study of Rajarhat-New Town Agglomeration, Kolkata, India

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Abstract

Rajarhat-New Town lies north of the East Calcutta Wetlands, a Ramsar site, and a natural sewage treatment plant for the Kolkata metropolitan area. However, the rapid growth of residential, commercial, and industrial developments has induced land use land cover (LULC) change that dramatically affects the inhabitants and the environment. Therefore, to identify development pathways, this study aims to measure land-use adjustments and land cover impacts on the socio-economic mobility of Rajarhat-Newtown. The earth observation data from 1991 to 2021 has been analysed to quantify the pattern of LULC changes using an Object-Oriented (OO) classification approach, integrated with the flexible cloud framework in the Google Earth Engine (GEE) platform to analyse the LULC. The final classification approach is adopted by combining the machine learning (ML) algorithms of Support Vector Machine (SVM) and Random Forest (RF). Principal Components Analysis (PCA) has been applied to the significant "Grey-Level Co-occurrence Matrix" (GLCM) indices to synthesise the textual data needed for the OO categorisation within a single band. From the results, negative changes have been identified for almost all the features concerning the base year of 1991. Furthermore, a time series analysis has been undertaken to monitor the spatial LULC changes between 1991 and 2021 at 10-year intervals over the region. Aside from that, special attention is being put on converting agricultural land to built-up areas, supporting the socio-economic transition of the study area's population. Based on the changing LULC pattern from 1991 to 2021, a prediction of LULC for 2031 has been executed for the study area. Conclusively, identifying LULC changes and their pathways has beneficial and detrimental impacts on the region's society, economy, and environmental sustainability.

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1. Introduction

Land can be classified into different divisions based on its quality, capability, grade, and potentiality[1]. Land use land cover (LULC) of any region reflects the utilisation of lands by the population living there. The changes in LULC occur for several reasons, which vary in different temporal and spatial scales. In such a context, land use planning (LUP) is essential for locating residences, agricultural zones, industrial zones, eco-sensitive zones, historical monuments, etc., to address environmental and anthropogenic risks [2]. Each classification of land has its importance; for example, agricultural land is essential in rural areas since it is the primary source of income. On the other hand, residential, commercial, and industrial sectors in metropolitan regions govern the region's economy [3]. According to Ramankutty and Foley[4], over the past three centuries, 1.2 million km^2 of forest and woodland and about 5.6 million km^2 of grassland and pasture have been transformed globally. At the same time, farmland has expanded by 12 million km^2. Agriculture or industry accounts for 10-15% of the transformed sections of the Earth's surface [5]. Thus, LULC change is an essential characteristic in global change, influencing the changes in the natural environment and accelerating human-induced activities [6].

Moreover, land degradation, which has become a major worldwide concern in the modern world, has occurred primarily due to climate changes, soil deterioration, and LULC change [7]. In addition to that, rapid urbanization in the region is further accelerating the land-use changes [3]. Since the mid-20th century, the apparent massive rise of the urban population forced most third-world nations toward sudden expansion of urbanisation. Because of that, policymakers faced numerous challenges in the management of the land, which ultimately triggered the misuse of finite land-based resources and environmental degradation [8]. As a global phenomenon, urban expansion is a process that occurs when a city occupies adjacent territory, resulting in socio-cultural changes in land-use patterns, demographic traits, and socio-economic life of the people who reside in the concerned area [9]. LULC change is a regionally prevalent and globally significant ecological trend. The changes in LULC have a substantial relationship with the future changes in Earth's climates and correspondingly more significant consequences for the eventual land-use changes [5].

Over the years, several researchers have conducted studies on LULC change. Anderson et al.[10] established a framework of a national LULC categorisation system designed to meet the needs of federal and state agencies. It maintained the overview of LULC throughout the United States on a standard foundation of classification in a broader approach. An assessment of the impact of changes in LULC is done by Toh et al. [11] on the socio-economic situation of the people of Mount Bambuco and Caldera in Cameroon, as a result of an increase in croplands, houses, and bare lands, and a reduction in grasslands and natural forest. Wu et al. [12] has studied the dynamics of land use, the spatiotemporal pattern of Ecosystem Service Value (ESV), and the driving factors responsible for the development in the study region located in the Hangzhou Metropolitan Area (HMA) in China. They found that human infiltration into ecosystems has resulted in a decline in regional ecosystem service functions. Krausmann et al. [13] analysed the relationships between LULC and socio-economic metabolism changes in Austria between 1950 and 1995 during the agricultural industrialisation era. The main focus was to achieve self-sufficiency, with the primitive focus of Austrian agricultural production policy being to reduce overproduction while still intensifying it. Long et al. [14] have detected changes in land use between 1987-94 and 1994-2000 in Kushan, Jiangsu province, China, that there has been a decrease in the areal percentage of paddy, dryland, and forest areas in both periods. Contrastingly, there has been considerable growth in the areal percentage of urban and rural communities and construction areas. Remote sensing technologies can effectively observe LULC change dynamics [15][16]. Long et al. [14] applied remote sensing and socio-economic data to analyse the characteristics, critical driving causes, and potential control strategies of land-use change in Kushan, Jiangsu province, China. They developed change matrices based on remote sensing-derived maps to identify changes in LULC through pixel-to-pixel comparison. LULC creation is a standard remote sensing data framework that depicts how land is used for several human activities, such as agriculture, residential sectors, or physical features of the Earth's surface (such as rocks, grasslands, and water bodies) [17]. Wu et al. [12] used GIS and remote sensing tools to extract information on changes in LULC from 1978 to 2008 using Landsat MSS/TM/ETM+ imagery.

Land-use change is directly related to and impacted by the livelihood options and opportunities of the people. The current study is based in Rajarhat Newtown, mainly located in North 24 Parganas, rapidly becoming urbanised. It influenced the region's changes in land use, population structure, and occupational structure [3]. Rajarhat, at various stages, became a legally planned development area, including the acquisition of vast areas of agricultural land and water bodies and their transformation into developed lands comprising a business market, industrial region, etc. Since 1995, the Government of West Bengal has been developing the area as a planned satellite new township from a peri-urban region. Its history and land acquisition procedure played an intrinsic role in the urbanisation process and the subsequent socio-economic consequences of the region, focusing on ecological and environmental degradation [18]. Many studies [9][19][20] were conducted based on the conventional LULC classification method for the region without considering the context of socioeconomic mobility. Therefore, the study aims to explore the nature of conversion that occurred within society, changing the occupational structure and the demographic structure of the inhabitants due to periodic changes in LULC, with a particular emphasis on the increase in the area under built-up lands that occurred between 1991 and 2021. For classification purposes, the study used the image segmentation method to integrate the Object-Oriented (OO) classification technique for finding spatial clusters with GLCM to calculate the cluster textural characteristics and two widely used machine learning algorithms (SVM and RF) for the penultimate classification. The outcomes of the study on LULC changes would be useful to understand the linkages with the socioeconomic mobility of the region. In addition, the study can add to the broader underlying causal relations of the LULC changes in the planned township, which will be helpful for the future perspectives of the urban-rural economy.

2. Materials and Methods

2.1. Study Area

The Rajarhat-Newtown agglomeration (fig. 1) is predominantly located in the North 24 Pargana and marginally in the South 24 Pargana districts of West Bengal, India. The latitudinal and longitudinal extension of the area is 22º30′32″N to 22º 38′ 03″N and 88º 26′ 29″E to 88º 32′ 57″E. Rajarhat-Newtown does have a total area of around 7212 hectares and is located to the north of the East Calcutta Wetlands (ECW) and northeast of the Salt Lake metropolitan region [3]. The Rajarhat-Newtown agglomeration has been developed as a satellite town of metropolitan Kolkata. It is considered West Bengal's rapidly growing planned satellite metropolis [19]. The yearly highest mean temperature in the study region is 38.5°C, the lowest average temperature is 17.4°C, and the annual rainfall is 1029 mm [21]. Rajarhat Newtown was designated as a township by the West Bengal Govt. in 1995 [19]. The township was meant to be constructed in a very planned and environmentally responsible manner. Consequently, the region was divided into distinct zones such as Action Areas I, II, III, and CBD [3]. As a result, the study area can be described as a peri-urban region of Kolkata. It has been a statutorily authorised development entailing the acquisition of a large portion of agricultural lands and water bodies for residential and industrial operations and infrastructure construction in the area.

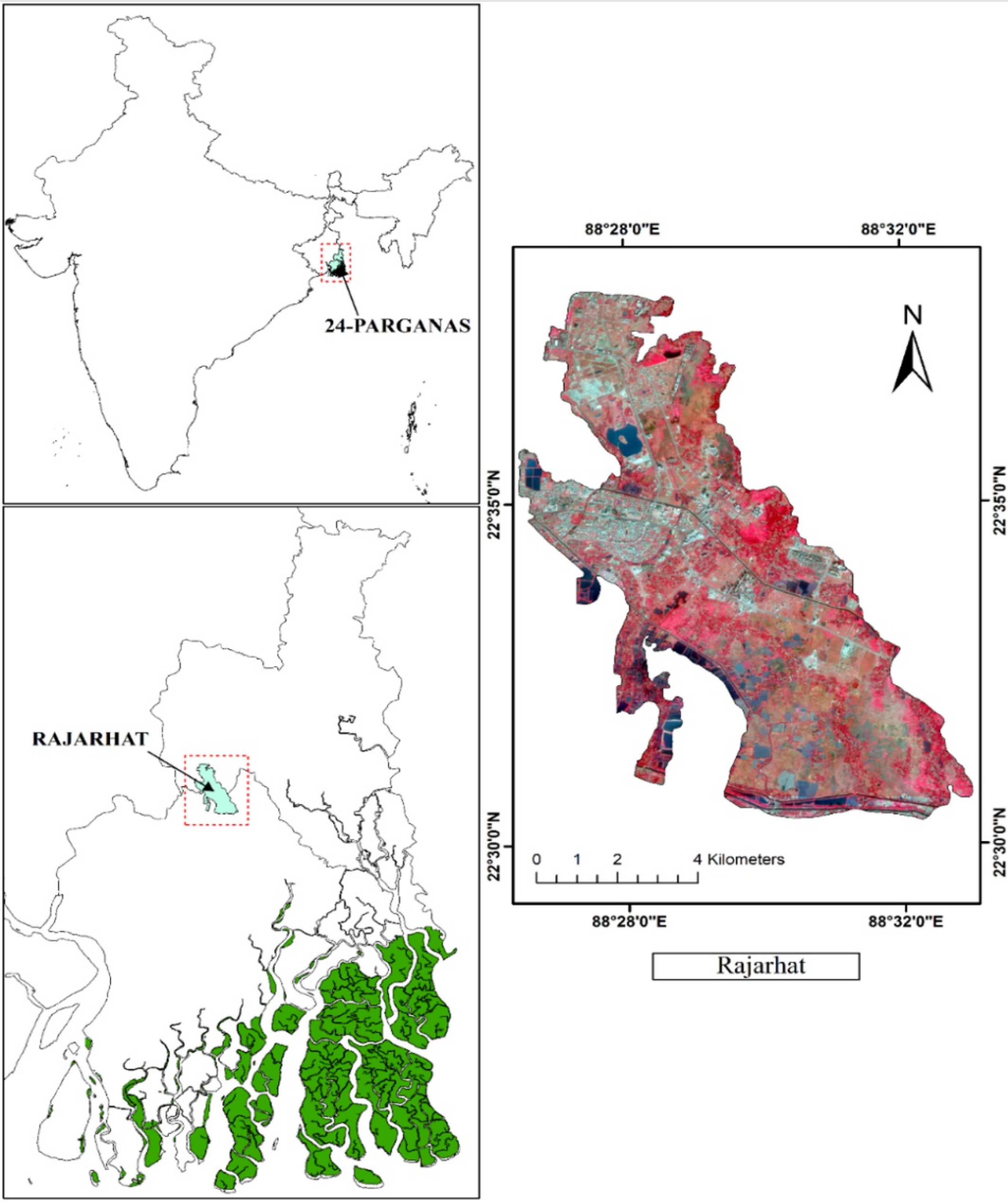

Figure 1. Location map of Rajarhat-Newtown agglomeration as the study area

Table 1. Details of the satellite-based datasets utilised for the current study

Satellite / Sensor	Date of Acquisition	Spectral Bands	Spectral Signature	Wavelength	Resolution
Landsat-TM	05.03.1991	Spectral Band 1	Blue	0.45 - 0.52	30
		Spectral Band 2	Green	0.53 - 0.60	30
		Spectral Band 3	Red	0.63 - 0.69	30
		Spectral Band 4	NIR	0.76 - 0.90	30
Landsat-TM	12.01.2001	Spectral Band 1	Blue	0.45 - 0.52	30
		Spectral Band 2	Green	0.53 - 0.60	30
		Spectral Band 3	Red	0.63 - 0.69	30
		Spectral Band 4	NIR	0.76 - 0.90	30
Landsat-TM	24.01.2011	Spectral Band 1	Blue	0.45 - 0.52	30
		Spectral Band 2	Green	0.53 - 0.60	30
		Spectral Band 3	Red	0.63 - 0.69	30
		Spectral Band 4	NIR	0.76 - 0.90	30
Landsat-OLI	03.01.2021	Spectral Band 2	Blue	0.45 - 0.51	30
		Spectral Band 3	Green	0.53 - 0.59	30
		Spectral Band 4	Red	0.64 - 0.67	30
		Spectral Band 5	NIR	85. - 0.88	30

2.2. Data

The multi-temporal and multi-spectral satellite data of Landsat-5 TM, Landsat-8 OLI/TIRS of various resolutions have been collected to utilise in this research of LULC technique analysis. The multi-spectral datasets of the satellite sensors specified above have been acquired for years 1991, 2001, 2011, and 2021. Table 1 illustrates the various spectral bands of satellite datasets with their acquisition dates, varied resolutions, and wavelengths utilised for the present research.

2.3. Training and Validation of Sample Datasets

The study area is characterized by a changing landscape mosaic comprising nine LULC classes. The built-up areas comprise rural and urban areas and other artificial structures. The croplands are mostly encompassed by annual crops, mainly paddy cultivation, and a few horticultural crops. Then there are the water bodies, including ponds, marshes, canals, and aquaculture fisheries. Then there are fallow lands, consisting of cultivable wastelands, green regions like shrub lands, and open fields. To assess the practicability and efficiency of methods, precisely 10 points were assigned to each class utilizing the GEE platform and the Landsat 5 (TM), Landsat 8 (OLI), and composite infrared layers. The high-resolution layer of Google Maps was used to gather training data. A total of 450 validation sites were generated randomly and followed by a manual selection procedure using the same foundational layers visually (Table 2).

2.4. Methodology: Classification and Accuracy Assessment

The whole workflow (Fig. 2) includes certain essential stages performed in a single GEE script. The chart in Figure 2 shows the original dataset's configuration, classification of LULC (in an OO approach), and the accuracy assessment procedure. The first phase of the methodology has been incorporated in a GEE script to facilitate a quicker categorization and accuracy assessment procedure. Consequently, the initial composite image requires fewer changes once generated than the following steps. Finally, the classification and accuracy assessment methods were integrated into a single GEE program. It comprises an OO method of classification that utilizes similar training data and uses either the SVM or RF classifier. The primary algorithmic method of RF classification includes the bootstrap sample technique; 2/3rd of the data is extracted as training samples, alluded to as in-bag data (IB). The remaining 1/3rd of the data, as validating samples, is indicated as out-of-bag (OOB) data, viable for calculating internal error [22]. This technique has been used widely in several studies [23][24][25]. Then the method of predicting the LULC of the study area for 2031 has been executed, as mentioned in Figure 2.

Table 2. Total number of validation points for each LULC class selected for the study

LULC Class	Field verification points
Rural Section	40
Urban section	35
Cultivated land	131
Lake/pond	23
Waterway	17
Aquaculture Pond	80
Vegetated Land	65
Shrubland	59
Total LULC sample	450

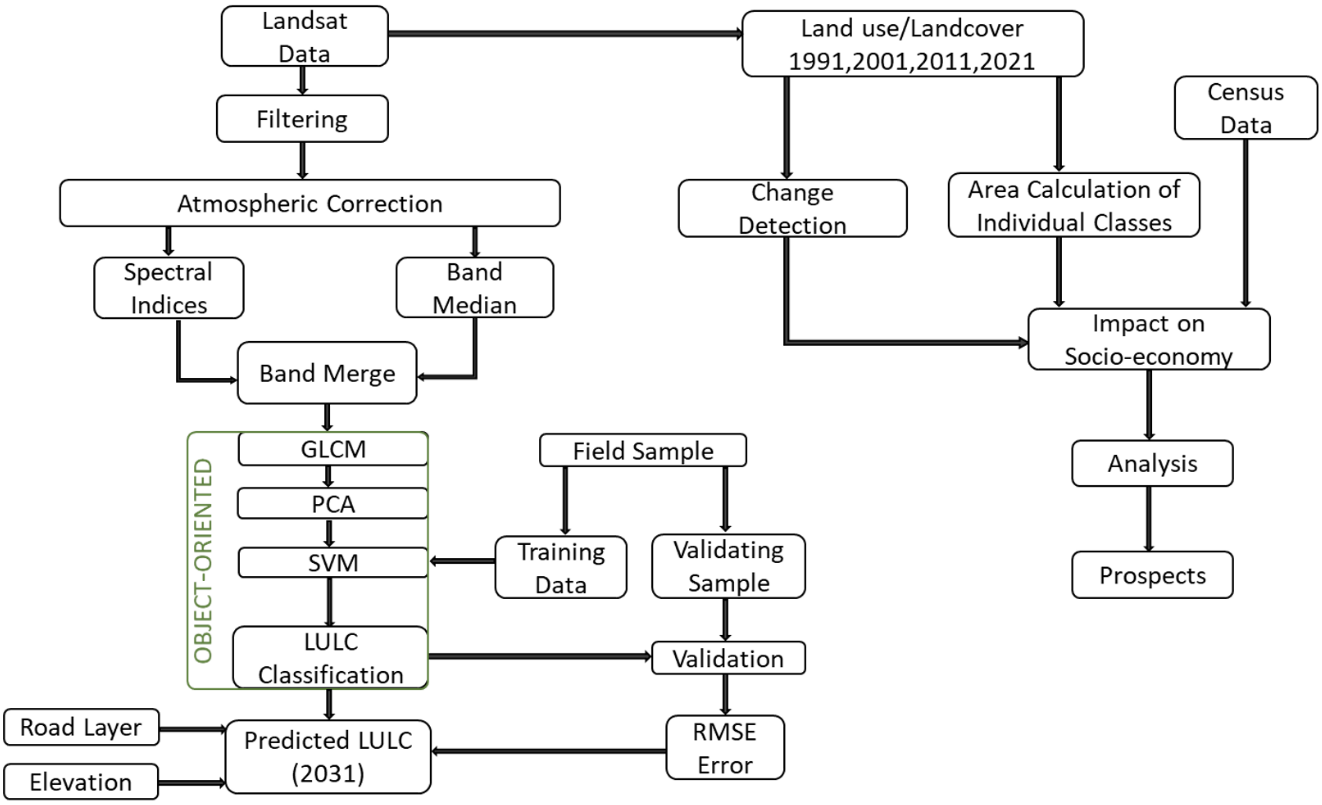

Figure 2. Flowchart depicting the methodological workflow of the current study

2.5. Dataset composition

In general, creating the initial dataset is indeed an essential step in any LULC classification. The Landsat 5 TM (1991, 2001, and 2011), Landsat 8 OLI (2021) dataset is built in GEE with filtered and cloud-masked imageries. The Bare Soil Index (BSI), Normalized Differential Vegetation Index (NDVI), and Normalized Differential Water Index (NDWI) are then computed for each picture. The NDVI index is widely used in monitoring land cover transitions [26], and it is used in the categorisation of LULC. Ac-cording to Singh et al.[27], this greatly improves classification accuracy. Because of its enhanced ability to identify bare soil and unoccupied areas, the BSI emphasises the contrast between non-cultivable and cultivable land [28]. NDWI is a comprehensive satellite-derived index that depicts temporal variations in water and wetness concentration in plant canopies over vast regions using the Shortwave-Infrared (SWIR) and Near Infrared bands (NIR). These different indices are commonly utilised to improve LULC categorisation [29][30]. Data enhancement is performed using the significant statistical dataset of NDWI, BSI, and NDVI to generate the bands comprised of the critical statistics of these indices helpful in accounting for seasonal changes in the LULC classes. The study area is characterized by a changing landscape mosaic comprising nine LULC classes. The built-up areas include rural and urban areas and other manufactured structures. The croplands are mostly encompassed by annual crops, mainly paddy cultivation, and a few horticultural and horticultural crops. Then there are the water bodies, including ponds, marshes, canals, and aquaculture fisheries. Then there are fallow lands, consisting of cultivable wastelands, green regions like shrub lands, and open fields.

2.6. Object-based Classification for LULC Changes

The classification approach of the OO method has been performed in GEE, each using SVM and RF classifiers alternately, as per the specific objectives of the current study. The algorithm requires this collection of inputs to perform the LULC classification. The GEE framework simplifies training data input (points or polygons) and inserts as many feature repositories (comprising additional geometries) as the required LULC classes. A buffer with a specified radius (10 m) was constructed around each site to increase the amount of regulated information. The training dataset from the LULC attribute in the "Newfc" feature compilation is used to train the selected classifiers. The validation point data collection may be uploaded and imported in different formats employing GEE or a GIS application. Validation points are included in the data set. The classification is conducted on the identical preliminary composite dataset, comprising training data previously produced. The OO classification method consists of a spatial clustering step that groups similar and adjacent pixels together, a following cluster-based texture indices calculation, and a final classification step. The principal LULC classes comprise urban areas, rural areas, ponds/lakes, aquaculture, canals, vegetation, croplands, and shrubland in the study area. Landsat 5 TM and Landsat 8 OLI satellite datasets were used to determine the spectral reflectance values of the LULC classes. After that, the mean reflectance among each category is calculated, and the spectral variations among the LULC classes are evaluated.

The spectral properties of the LULC classes were determined from different satellite datasets using the blue, green, red, and near-infrared bands. The LULC classes utilized in this research are used to calculate NDVI, NDWI, and BSI for various image datasets. The NDVI of satellite datasets has been used to track land cover changes and classify LULC. Shrublands, croplands, built-up regions, and water bodies (ponds, aquaculture, and canals) have distinct NDVI values. In the present research, the NDVI is utilized to monitor land cover changes and to classify LULC. BSI has highlighted the distinction between agricultural and non-agricultural terrain because of its improved capacity to detect bare soil and open areas. The NDWI is a contemporary satellite-derived index used to reveal changes in plant canopies' surface water and moisture content over large areas. In the current study, these indices improve LULC classification and are regarded as feature characteristics derived from the satellite image. Aside from that, Digital Elevation Model (DEM) data with a spatial resolution of 30 m has been obtained from the Shuttle Radar Topography Mission (SRTM) and is being used to generate elevation, slope, and aspect data, which will be used as surface feature attributes for LULC class recognition and mapping.

The GLCM algorithm, as previously mentioned, takes as input 8-bit grey-level images. In the code, this picture is created by linearly combining the green, red, and near-infrared bands of the original or initial composite images, as seen below (Eq. 1)

$$Gray = (0.3 * NIR) + (0.11 * GREEN) + (0.59 * RED)$$

Following proper normalization, a PCA comprised of the essential parameters of GLCM, as determined by Hall-Beyer (2017), was utilized in this work to produce a single representative band (PC1) that generally comprises the vast majority of the texture-based data.

i. **Contrast:** It is calculated using the variation in local grey levels. (Eq. 2).

$$Contrast = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \qquad (2)$$

ii. **Mean**: It estimates the mean of the cumulative grey level distribution of the image. (Eq. 3).

$$\mu_i = \sum_{i,j=0}^{N-1} i\left(P_{i,j}\right) \qquad u_j = \sum_{i,j=0}^{N-1} i\left(P_{i,j}\right)$$

iii. **Variance**: It assesses the distribution of grey-level dispersion to emphasize the visual borders of land-cover segments (Eq. 4).

$$v\left(\begin{smallmatrix}2\\ i\end{smallmatrix}\right) = \sum_{i,j=0}^{N-1} P_{i,j}(x+a)^n \qquad v\left(\begin{smallmatrix}2\\ i\end{smallmatrix}\right) = \sum_{k=0}^{n} P_{i,j}(i-\mu_i)^n$$

iv. **Homogeneity:** This measure assesses grey-level distributions' smoothness (or homogeneity). (Eq. 5).

$$Homogenity = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1} + (i-j)^2$$

v. **Entropy:** This metric approximates the degree of disorder among pixels in the image (Eq. 6).

$$Entropy = \sum_{i,j=0}^{N-1} [-1_n P_{i,j}]$$

vi. **Correlation**: This parameter determines the linear relationship of the grey levels in neighboring pixels. (Eq. 7).

$$Correlation = \sum_{i,j=0}^{N-1} \left[\frac{(i-\mu_i)(i-\mu_i)}{\sqrt{(\delta_i^2)(\delta_i^2)}} \right]$$

vii. **Angular Second Moment**: This metric measures the homogeneity or energy of an image's grey level distribution. (Eq. 8).

$$ASM = \sum_{I,J=0}^{N-1} P_{i,j}^{\ 2}$$

2.7. Analysis of secondary data

Specific secondary data has been obtained for the study, and a base map of the district of North 24 Parganas with blocks has been obtained to define the study area boundary at (http://www.north24parganas.gov.in/)[31]. The Rajarhat Newtown project area map was obtained from the West Bengal Housing Infrastructural Development Corporation's official website (https://www.wbhidcoltd.com/)[32]. The satellite imageries of Landsat 5 TM and Landsat 8 OLI were obtained from the United States Geological Survey's (USGS) website (https://earthexplorer.usgs.gov/)[33] at 10-year intervals from 1991 to 2021. Field surveys were conducted for this study to collect primary data. The surveys were carried out utilizing mobile GPS to gather ground truth points (GTP) based on the physical and cultural characteristics of the studied region. Secondary data regarding the study area of the Rajarhat-Newtown area was collected from various sources, including census data [34][35] and particular literary references. The secondary data is mainly related to the demographic structure of the study area. The decadal period (2001-11) data was collected covering various aspects like rural-urban, male-female population composition, working and non-working population composition, occupation structure, etc. The main aim of collecting these data is to analyze the socio-economic change that occurred solely due to changes in land use and land cover of the study area.

3. Results and discussion

3.1. Decadal changes in LULC

Several techniques are to be put to use to comprehend the pattern of LULC properly. These techniques have also been discussed before. The LULC for the study area is then calculated using the Object-Oriented classification approach with nine distinct classes. The area covered by each LULC class from 1991 to 2021 was then calculated per sq. km and percentages, as shown in table 3.

Table 3. Year-wise areal coverage of each LULC classification from 1991-2021 over the study area

Class	1991		2001		2011		2021	
	Area		Area		Area		Area	
	sq.km	%	sq.km	%	sq. km	%	sq. km	%
Village	0.97	1.36	1.38	1.94	1.78	2.50	3.87	5.43
Vegetation	29.53	41.47	24.85	34.90	17.19	24.14	16.24	22.81
Town	0.21	0.29	2.98	4.18	6.39	8.97	14.68	20.62
Scrubland	20.52	28.82	15.73	22.09	8.74	12.27	6.57	9.23
Open land	4.36	6.12	3.8	5.34	1.65	2.32	0.43	0.60
Crop land	8.98	12.61	13.53	19.00	19.66	27.61	15.42	21.65
Aquaculture	4.96	6.97	7.12	10.00	12.49	17.54	10.84	15.22
Pond	0.32	0.45	0.61	0.86	2.31	3.24	2.19	3.08
Canal	1.36	1.91	1.21	1.70	1	1.40	0.97	1.36

The data in table 3 has been depicted in inline diagrams (Fig. 3a) and a deviation bar diagram (3b), showing the change from 1991-2021 in the area occupied by each LULC class in the study area.

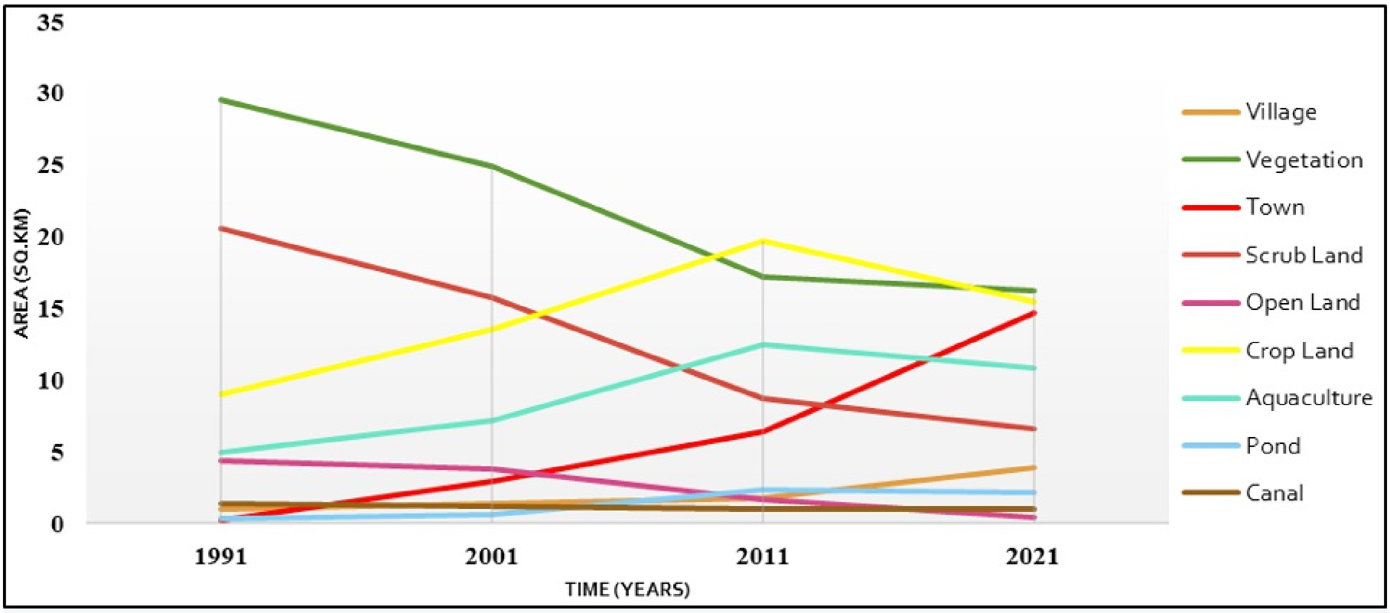

Figure 3a. Line graphs representing each LULC class show the change in 1991-2021 over the study area

As per table 3 and figures (3a, 3b), the changes in area covered by each LULC class of the study area are depicted. The croplands, comprising cultivated lands under different types of crops (paddy, wheat, potatoes, pulses, and oilseeds are the principal crops of cultivation), occupied 8.98 km^2 (12.61 %) of the study area in 1991, steadily increased to 13.3 km^2 (19 %) by 2001, and 19.66 km^2 (27.61%) by 2011. The area under croplands has substantially decreased by 5.95% in the current year, constituting 15.42 km^2 (21.65%) of the study area. The major portion of the agricultural land has been predominantly under paddy cultivation. Next, the water bodies, comprising the classes of ponds and canals, occupied 1.68 km^2 (2.31%) of the study area in 1991, increased consistently to 1.82 km^2 (2.6%) in 2001, and 3.31 km^2 (4.65%) in 2011. Currently, in 2021, the water bodies cover 3.6 km^2 (4.44%) of the study area. Then, the class of aquaculture patches occupied the majority of the water bodies in the study area, occupying 4.96 km^2 (6.97%) of the study area in 1991. As per table 2 and figure 3 (a, b), more water bodies of the study area are brought under aquaculture with progressing time. The area under aquaculture increased rapidly to 7.12 km^2 (10%) in 2001 and 12.49 km^2 (17.54%) in 2011. In 2021, there has been a decrease in the area (10.84 km^2) under aquaculture by 2.32% from 2011 due to rapid urban expansion, illustrated in figure 4.

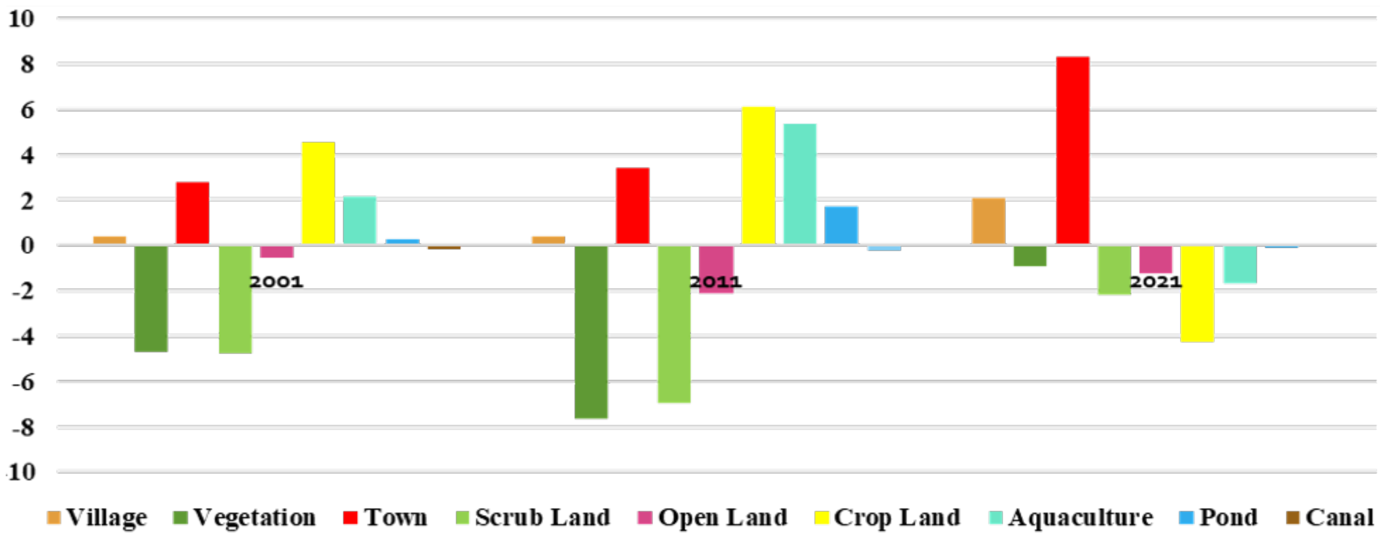

Figure 3b. Deviation bar diagrams showing the percentage change in area covered by each LULC class in 1991-2021

Then the class of vegetation depicting the land covered by natural vegetation predominantly occupied 29.53 km² (41.47%) of the study area in 1991, has steadily decreased to 24.85 km² (34.9%) by 2001, 17.19 km² (24.14%) in 2011. In 2021, the vegetation area further decreased (16.24 km²), attributing to the decline in the area by 26.9% from 1991. The rapid expansion of the built-up area is the main reason behind the decline in the area under vegetation of the study area, as per Figure 4. Then comes the class of scrublands, often referred to as shrublands, heathlands, or chaparrals, a variety of plant forms with the common physical trait of shrub dominance (Smith 2009). Scrublands had a predominant areal coverage of 20.52 km² (28.81%) of the study area in 1991. After 1991, the areal coverage of scrublands has substantially decreased to 15.73 km² (22.09%) in 2001, 8.74 km² (12.27%) in 2011, and 6.57 km² (9.23%) in 2021. This drastic reduction in the areal coverage of scrublands is mainly because the shrublands are converted to croplands and built-up area depicted in Figure 4. Then comes the class of open lands, often referred to as the bare land with no crops, including barren lands, vacant lands with green and open space. Open lands had an areal coverage of 4.36 km² (6.12%) of the study area, which decreased to 3.8 km² (5.34%) in 2001, 1.65 km² (2.62%) in 2011, and 0.43 km² (0.63%) in 2021. The reduction in the areal coverage of open lands has undergone conversion to croplands and built-up areas. The built-up area is subdivided into village and town, as shown in Table 2 and Figure 3 (a, b). Rajarhat's village area had an area coverage of 0.96 km² (1.36%) of the study area in 2001, 1.38 km² (1.96%) in 2011, 3.8 km² (2.62%) in 2011, and 2.50 km² (3.87%) in 2021. In 1991, the area under the town (0.211 km²) was less than that under the village. However, the town expanded more rapidly than the village. The town's area was 2.98 km² (4.18%) in 2010, and it rose to 6.98 km² (8.97%) in 2011. By 2021, there will be a significant rise in urbanization (22.8 km²) in the study area. As a result, the area covered by the town has increased by 20.32%, as shown in Figure 4.

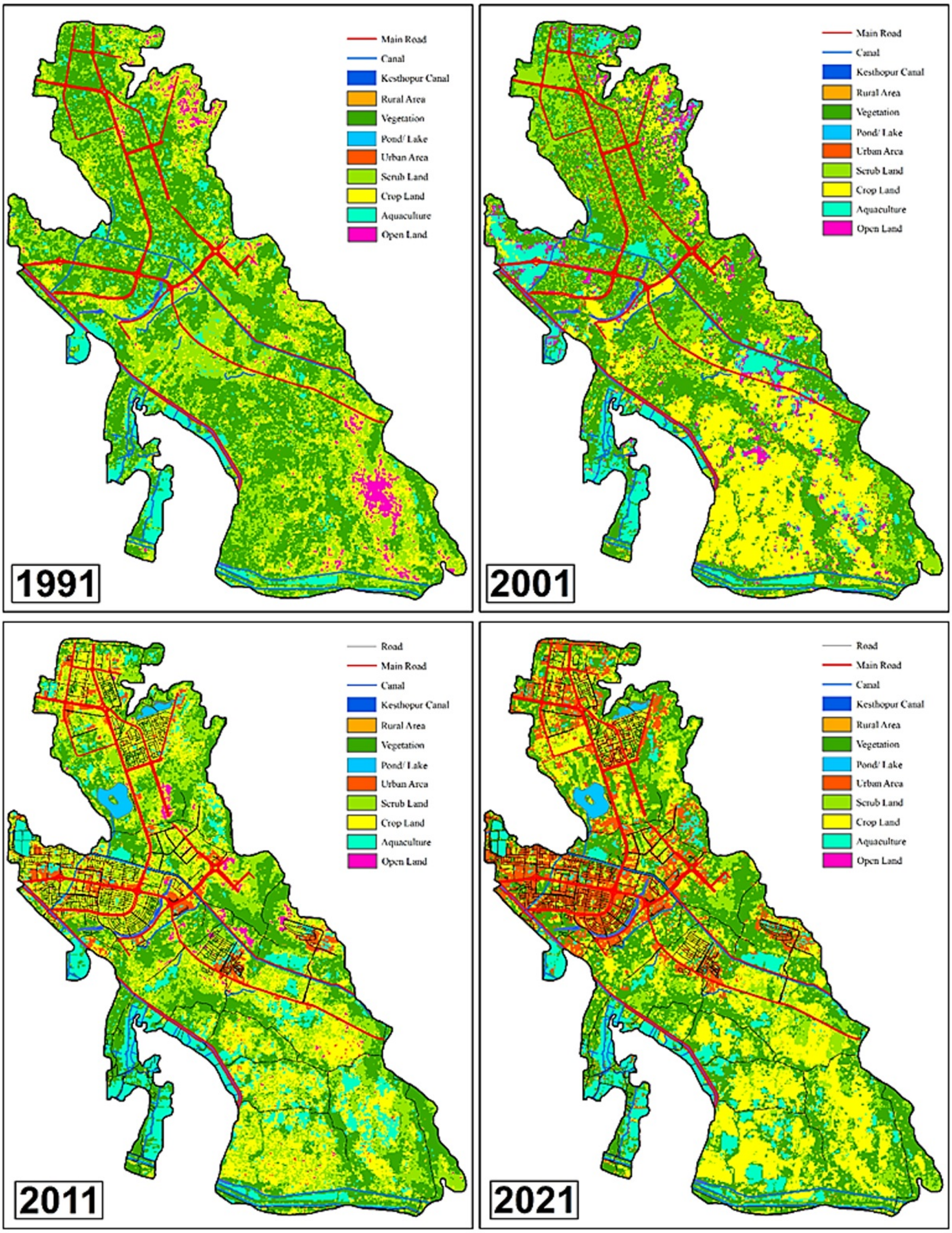

Figure 4. LULC maps of Rajarhat-New Town area using Object-Oriented classification method for the years 1991, 2001, 2011, and 2021.

Figure 4 shows the classified LULC outputs of the study area during 1991, 2001, 2011, and 2021, using the Object-Oriented classification approach. It can be observed from the classified outputs of the study area in Figure 4 that the built-up area has increased drastically from 1991 to 2021. The built-up growth area has mainly concentrated in the northern and northwestern regions of the study area. Among the built-up areas, the urban area has expanded tremendously, which led to the formation of Rajarhat-Newtown as a satellite city of the Kolkata Metropolitan Area. The classified outputs of 2021 in Figure 4 show that the urban area is also starting to extend toward the southern portions of the study area. As far as the other LULC classes of the study area are concerned, the south section of the study area is mainly concentrated with the landscapes of cropland and scrublands, with patches of Aquaculture, Ponds/Lakes, and canals. The classified output of 1991 shows patches of open land in the southern portion, which diminished by 2001 because of conversion into croplands. The output of 2001 indicates that there were concentrations of aquaculture ponds in the northwestern part of the study area, which reduced in 2011 and was fully converted into the urbanized built-up area in 2021.

3.2. Prediction of LULC

As mentioned in the workflow chart (Fig. 2), based on the time frame (1991-2021) of the current study, the prediction of LULC has been executed. The prediction has been performed by following the abovementioned methods in Figure 2. Apart from those methods, for the prediction process, the study area's road layers and elevation dataset have been incorporated for predicting the LULC of the study area for the year 2031. Figure 5 shows the predicted LULC of the study area during 2031 and shows that the urban built-up has rapidly expanded in the northern portion of the study area, at the cost of open spaces and scrublands. In Figure 5, the urban built-up is getting extended toward the southern part of the study area. As per Figure 5, the roadways are developing in that portion, leading to more urbanisation in the Rajarhat-Newtown area.

3.3. Accuracy assessment of LULC classification

Evaluation of Accuracy is a key step forward in processing remotely sensed data. It establishes the data estimation of the subsequent information to a user. Productive use of geo-data is only conceivable if the nature of the information is identified. The Accuracy assessment of the land use and land cover map of the study area from 1991-2021 using Object-Oriented Classification is executed by measuring the four types of accuracy, i.e., Producer's Accuracy (PA), User's Accuracy (UA), Overall Accuracy (OA), and Kappa Coefficient (K). The main aim is to quantitatively examine how successfully the pixels were assigned to the right land cover classes. Naturally, variables such as the characteristics and reliability of satellite data, the dispersion of validation locations, and the classes used for LULC classification may impact accuracy measurement. The code used the same techniques to evaluate and compare all classes. Table 1 shows the reference and classified values of individual LULC classes for calculating PA, UA, OA, and K. As per Table 4, the percentage range of PA of LULC for 1991 is 70.6 - 100%, 2001 (70.6 - 96.6%), 2011 (73.3 - 94.7%), and 2021 (70.2 - 100%). Then the percentage range of UA of LULC for 1991 is 72.7% - 100%, 2001 (81.7% - 98.3%), 2011 (80.6% - 94.7%), and 2021 (76.56% - 100%). If a comparison is made between the percentage ranges comprising the UA and PA percentages of the LULC, it can be said UA is more efficient than PA. In the case of OA and K statistics, the LULC of 2021 is more accurate than the LULC of another year.

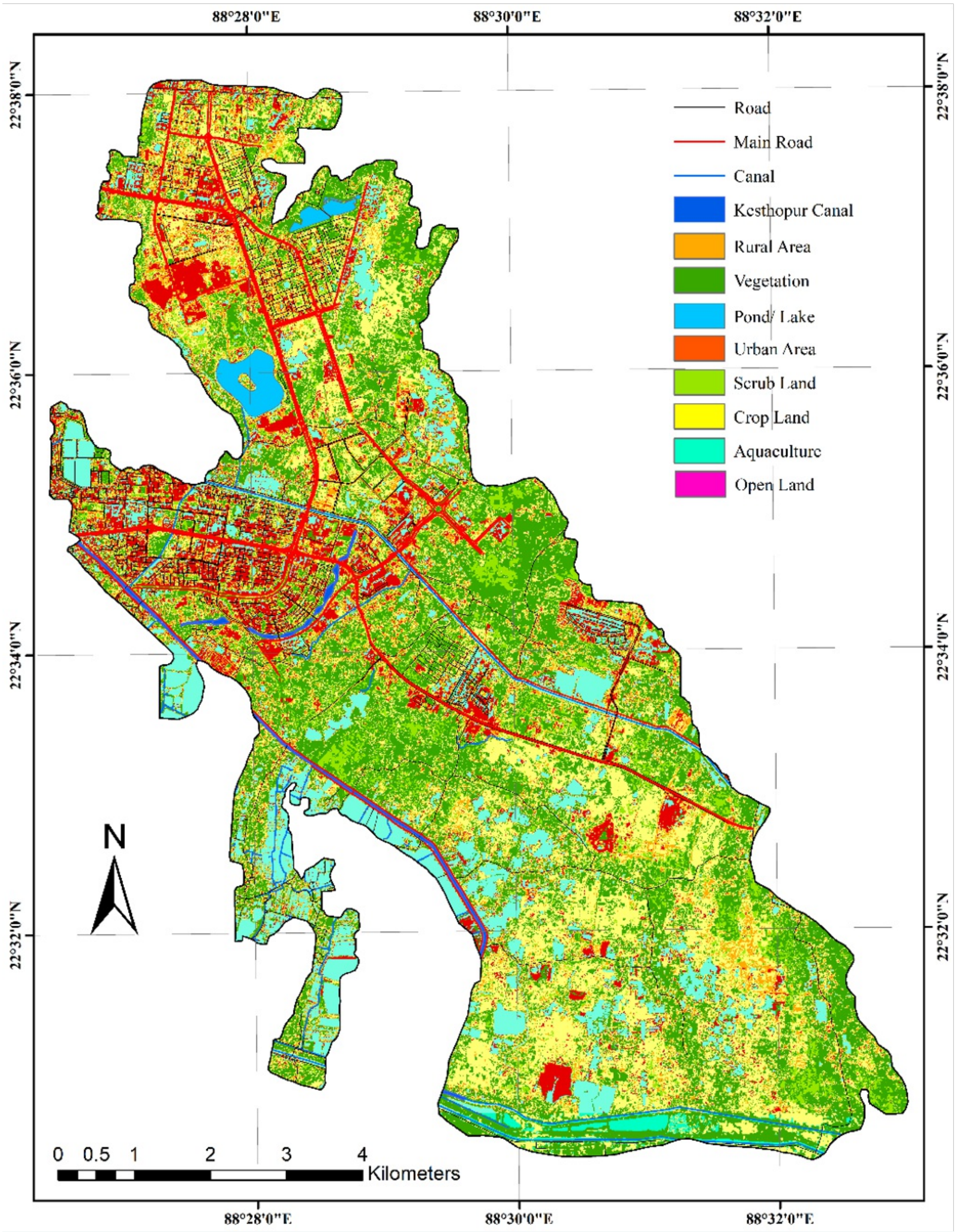

Figure 5. Predicted LULC map of the Rajarhat-Newtown area for the year 2031

4. Urbanisation policy and its influence on LULC

The Rajarhat-Newtown area was announced by the Govt. of West Bengal on June 1, 1995. It was a part of the master plan involving the spatial transformation and evolution of peri-urban areas of Kolkata, mainly for urban expansion to address the rising population pressure in the metropolitan area. The Rajarhat-Newtown was a part of the government's strategy to develop townships in the peri-urban areas around Kolkata Metropolitan Area (KMA), like Baisnabghata-Patuli Township, East Kolkata Township, and Rajarhat Newtown. The State Govt. enlisted five organizations (including the "Kolkata Metropolitan Development Authority," the "Indian Institute of Technology – Kharagpur," the "Division of Housing, Government of West Bengal," the "West Bengal Housing Board," and "Development Consultants Constrained") to prepare an ideal design, an expert land use/land cover design, a traverse study report, a draught venture report, natural effect evaluation and money related suitability reports, interior illustrations, urban foundation schemes, and plans, etc. [36]. The New Township Project under the ward of Rajarhat Block under North 24 Parganas District and Bhangore-II Block of South 24 Parganas District in the North-East of Kolkata involves 7089.72 acres of land. Until March 2013, a total of 6839.31 acres of land had been secured by the respective land acquisition collectors, North and South 24 Parganas districts, for the New Town Project. The rest of the land, i.e., 250.41 acres, was acquired from individual landowners [32].

Table 4. Classified areas of each LULC class to calculate PA, UA, OA, and K

Class	1991		2001		2011		2021	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Village	78	97.9	90.3	87.9	86.2	90.3	99.28	76.56
Vegetation	88.9	72.7	86.4	98.3	86.1	86.1	98.15	91.89
Town	70.6	83	84.1	84.1	93.5	82.7	77.54	81.42
Scrub Land	93.8	88.4	87.2	81.7	83.3	80.6	76.32	96.42
Open Land	100	100	96.6	96.6	94.7	94.7	100	100
Crop Land	96.3	100	93.5	95.6	88.9	88.9	98.31	78.65
Aquaculture	82.7	92.9	84	85.7	73.3	91.7	82.95	95.01
Pond	82.3	83	70.6	85.7	84.6	84.6	70.2	83.97
Canal	86.57	89.73	85.3	87.9	85.7	94.7	82.7	83
Overall accuracy	91%		87%		88%		91.69%	
Kappa statistic (K)	0.89		0.85		0.87		0.95	

However, it was one of West Bengal's most fertile areas. Aside from habitation, most, if not all, land is used to produce three to four crops per year [18]. The Keshtopur, Bagjola, and three other canals supplied enough water to irrigate this land. Prior to the land acquisition of the township project, 69.50% of South 24 Parganas, and 68.26% of North 24 Parganas were used for agricultural purposes (see figure 6)[37]. The socio-political and economic interests of policymakers played a crucial role in LULC during the initial phase of the township development, though the characteristics of the land (see table 5) selected for the project area were appropriate for agricultural land; however, policymakers ignored the facts, which is yet another critical aspect to look into to understand policy influence in LULC.

Table 5. Land use characteristics of the project area

District	Total land Procured (ha)	Areal percentage of land	Agriculture lands (in ha)	Agricultural Lands (%)	Non-cultivable Lands (ha)	Non-cultivable Lands (%)
North 24 pgs.	2818.5	91.65	1923. 91	68.26	894.59	31.74
South 24 pgs.	256.5	8. 35	178.27	69.5	78.23	30.5
Total	3075	100	2102.18	68. 36	972 .82	31.12

Source: *EIA report 1999*[38]

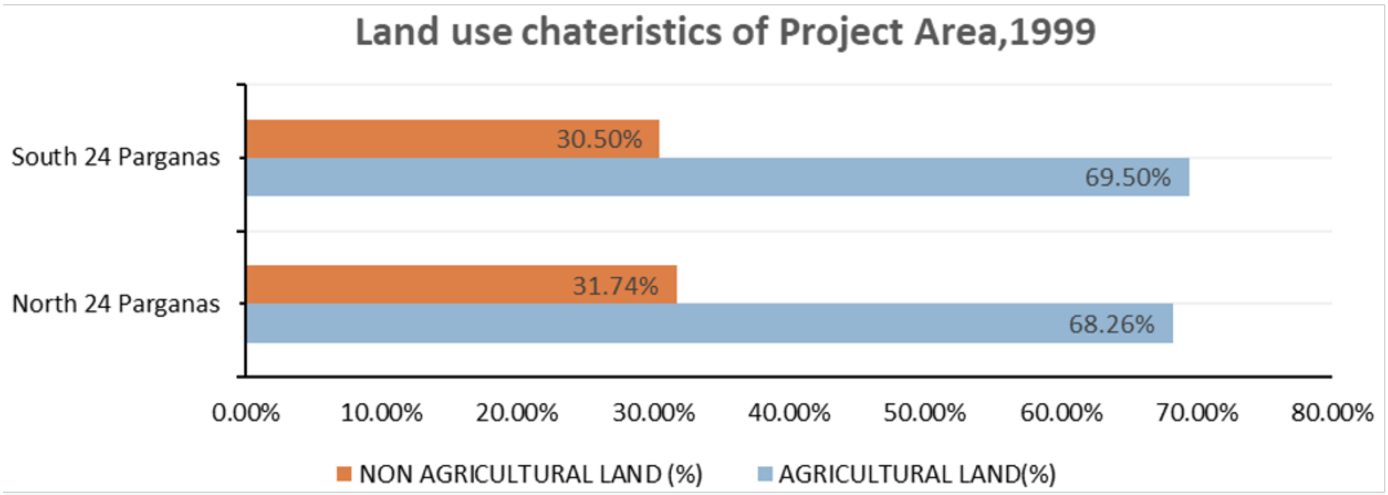

Figure 6. The representation of land use and land cover characteristics during land acquisition.

With the endorsement of the new township plan of the state government, the pattern of landholding was also drastically changed as land brokers financially influenced farmers to purchase their land [18][19][20][21][22][23][24][25][26][27][28][29][30][31][32][33][34][35][36][37], which changed the entire scenario of landholding patterns. To understand further, the land changed patterns are arranged into two expansive composes based on the profession of the landowner (see table 6). Sizes of the land possessions were negligible as the land proprietors got their territory because of the land change program. Almost 98% of proprietor cultivators were occupied with the development, albeit the number of non-cultivator individuals was relatively high. A double sort of economy genuinely existed here before working in the township.

Table 6. Landholding pattern of the study area in 1999

Number of landowner cultivators				Number of landowner non-cultivators			
Less than 3 acres		More than 3 acres		Less than 3 acres		More than 3 acres	
Number	%age	Number	% age	Number	% age	Number	% age
6448	98.08	126	1.91	12209	99.55	54	0.44

Source: *EIA report 1999*[38]

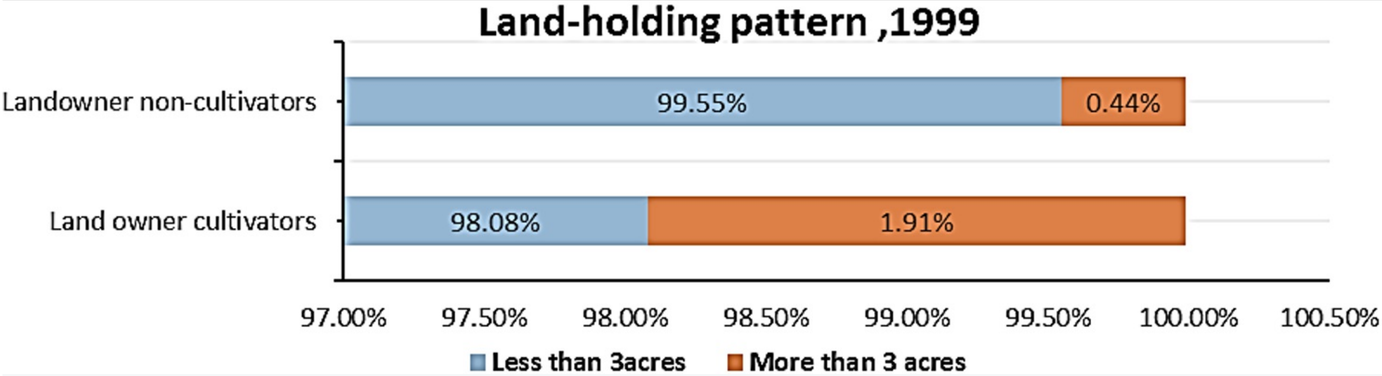

Figure 7. Landholding pattern of the study area at the land acquisition period (1999).

Karmakar [18] states that urban edges are "another player" in urban improvement and have analysed how the improvement of townships around the wetland would harm its biological system in the distant future. In the 2001 census, Rajarhat included 39 census villages and one census town [34]; after a decade, in the 2011 census, seven more census towns were added. Looking into the pattern of the changes, it can be noticed that Rajarhat has changed its characteristics from a common farming region to an urban territory (see Table 7). The urban populace in 1981 was 67,626, whereas the provincial populace was 95,567. In this way, plainly amid the 1980s, 41.43% of the populace was under the urban zone. In 2001, the urban populace ended up being 66.75% (Directorate of Census Operations West Bengal 2011). Initially, the Rajarhat district conceptualized urban development in 1971. The same year, Krishnapur Urban Agglomeration had formed three non-municipal developments (i.e., Krishnapur, Jyangra, Arjunpur) with 11.9 sq. km holding just 33,360 urbanites. From 1971 to 1981, three more urban areas were added in the non-municipal zone. The data (presented in Table 7) shows that urban development inside this period was more than double, though the urban area development was simply 12%. The entire situation changed radically from 1991 to 2001. The urban populace ricocheted up to 2.5 times since 1991. Within this decade, all the urban territories of Rajarhat converged under a single region, i.e., the Rajarhat-Gopalpur region. The decadal development rate of the urban populace inside this time span found the highest differences with the other two decades [9].

Table 7. Decadal changes in the demographic characteristics and area of the study area

Census year	Population			% of urban population of total population	Urban area in sq. km	% of urban area to total area
	Total	Rural	Urban			
1971	128478	95118	33360	25.97	11.9	14.89
1981	163193	95567	67626	41.44	13.3	16.65
1991	258358	138708	119650	46.31	17.43	21.81
2001	417192	138652	278540	66.77	36.54	45.73
2011	592,737	189893	402844	67.96	42.56	47.89

Source: *Primary Census Abstract, Census of India, 1971–2001*[34]

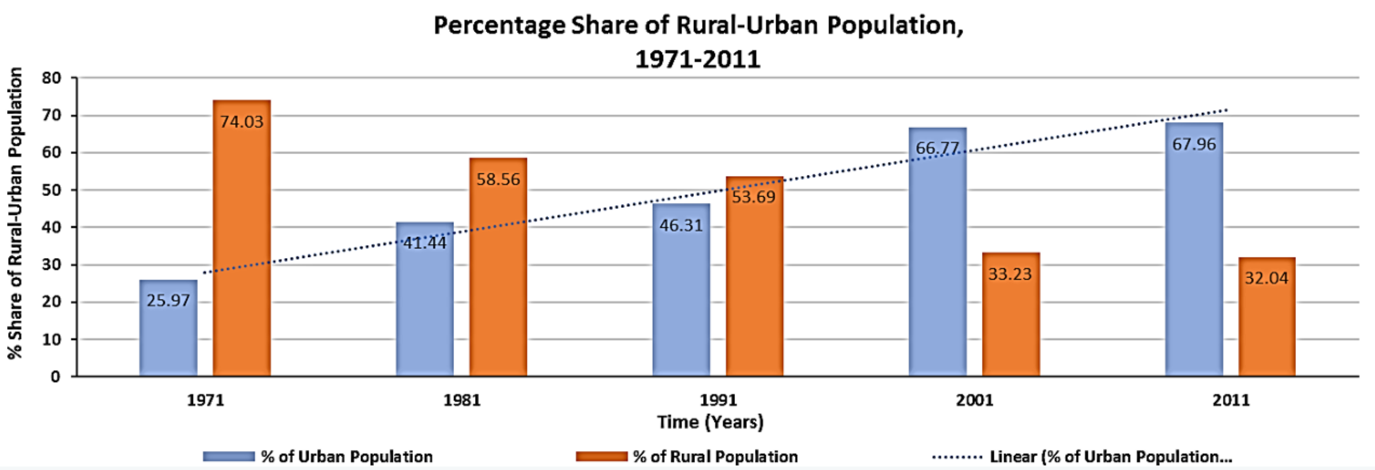

Figure 8. The representation of percentage growth of urban population in Rajarhat area between 1971-2011 [35]

It can be observed from the graphical representation of the percentage of the rural-urban population through the census years (1971-2011) that the urban population percentage was less than the rural population from 1971 to 1991. There was a gradual increment of the urban populace and a decrease of the rural populace, but the percentage of the rural populace was always higher than the urban populace. However, the scenario shifted after the government conceptualised the satellite township in Rajarhat. With the endorsement of the government's strategic plan, the land use character started changing, which gave gradual impetus to the increment in the urban populace. So, the gradual conversion of the rural populace to the urban populace took place from 1991 to 2011, sowing a rising trend indicating urban population growth. The development of the aggregate populace from 1981 to 1991 was substantially higher than from 1991 to 2001. The year-wise development of the total populace during 1981 to 1991 was 7.52%, while it was just 4.58% during the following decade. The all-inclusive legislative strategy conceptualised a township here no less than three times greater than the neighboring Salt Lake. As indicated by the administrative proposition, the township's growth is expected to reach out to the great south of the state, i.e., up to the Sundarbans close to the Bay of Bengal.

Table 8. Shift of occupation pattern in the Rajarhat-Newtown area between 1981-2011

Occupation types	Urban area						Rural area					
	1981		2001		2011		1981		2001		2011	
	Number	%	Number	%	Number	%	Number	%	Number	%	Number	%
Cultivators	126	0.74	580	0.62	372	0.26	5164	22.43	4261	9.70	2798	4.84
Agriculture laborer	573	3.42	326	0.35	349	1.80	6531	28.37	7217	16.43	2473	4.27
Household industry	355	2.10	1583	1.65	2192	1.57	537	2.33	2519	5.73	1653	2.85
other	15831	93.74	91512	97.35	136697	97.90	10791	97.90	2991	68.12	50904	88.02
Total worker	16889	100	94001	100	94001	100	23023	100	43918	100	57.828	100

Source: *Census of India 1981, 2001, and 2011*[34][35].

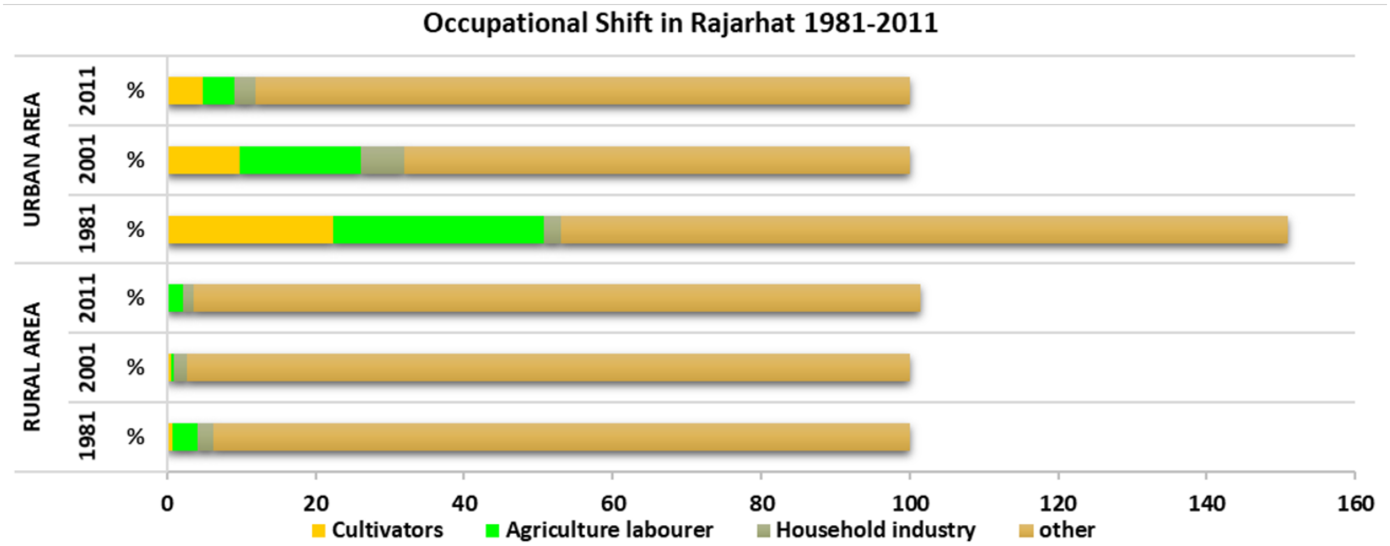

Figure 9. The representation of the shift in occupation in the study area between 1981-2011 [35]

Further to understand in more detail, firstly, in 1999, 21 mouzas of the place known as Rajarhat were occupied for the New Town venture. So far, roughly 3087 hectares of the places known as Rajarhat and Bhangore were occupied. The State Government had allocated (April 1996) land for obtaining for NTP (New Town Project) to the West Bengal Housing Board. In this way, the West Bengal Housing Infrastructure Development Corporation Limited (WBHIDCO Ltd Company) was incorporated (April 1999) to develop NTP as an ultimately owned Government organization. So, NTP was executed in four stages, viz., Action Areas (AA) – I, II, III, and IV [32]. Given the nonappearance of an urban body inside New Town for operation, the state government endorsed the New Town Kolkata Development Authority Act 2006 under the West Bengal Municipal Act. Later, the New Town Development Authority was formed in Jan 2009. Later, the company (WBHIDCO Ltd) had requested to procure extra zones, i.e., 19 mouzas of South 24 Parganas and three mouzas of North 24 Parganas for further city extension. However, extra zones have not yet been obtained considering the changing land procurement approach of the present West Bengal Govt. [18]. With this changed legislature and governance structure, the urbanization trend Rajarhat experienced numerous financial changes. Such changes include the literacy rate, availability of paved and metal roads, power facilities, and so on; apart from such changes, occupational movements are one of the major changes that have happened due to the urbanization process in Rajarhat. As it is now another IT hub of West Bengal, many big corporates have set up their offices in Rajarhat. The education rate increased 4.25% from the 1991 level in 2001. Many villages with metal and paved roads were also increased to 38 in 2001; 28 and 22 villages had metal and paved roads in 1991. The availability of power also rose from 15 villages in 1991 to 33 villages in 2001. Aside from this, people in this area are experiencing changing business options. Table 8 shows how the occupation options have changed over three decades. Cultivators and agricultural workers have contracted both in the urban and rural areas. Non-agrarian employment opportunities have increased by 20% in the rural zone throughout the decades. On the other hand, the openings for cultivator and agriculture work have decreased by 12.73% and 11.94% in rural areas**.**

Table 9. Rate of decadal growth of working population in Rajarhat-Newtown

Population growth	1981-91	1991-2001	2001-2011
Total working Population growth	-0.51	8.16	4.29
Urban working Population growth	1.85	13.58	4.82
Rural working Population growth	-2.83	2.17	3.16

Source: *Census of India 1991, 2001, and 2011*[34][35]

The yearly development rate of the working populace (main and marginal) of Rajarhat was higher during 1991 and 2001. The development of the provincial working populace was negative in 1981 and 1991. The prime purpose for the development of the utilized populace is that individuals are landing positions in different fields like development specialists and other enormous corporations. Furthermore, the changing pattern could be noted from the formal to the non-formal sector.

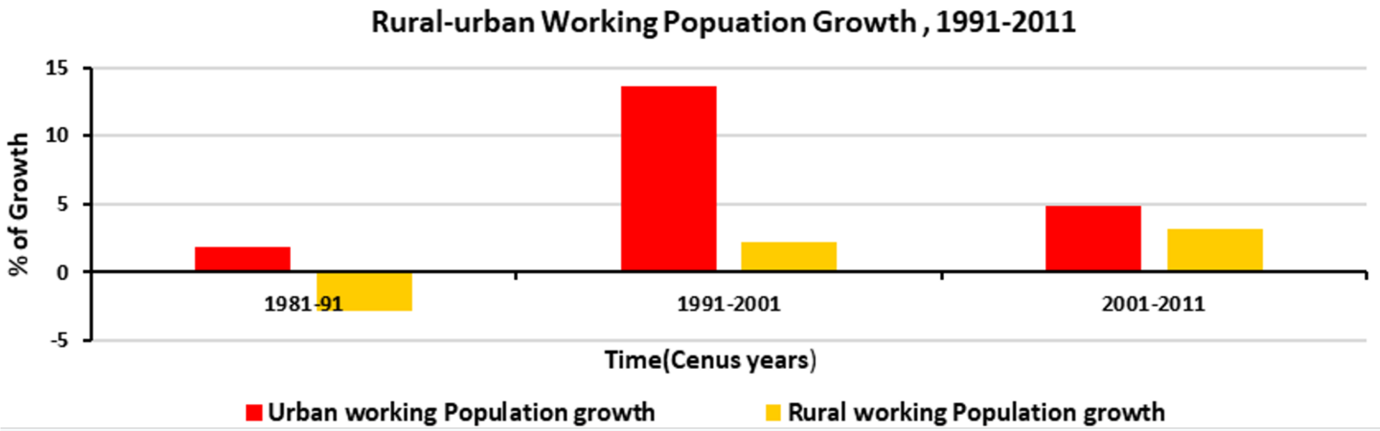

Figure 10. Showing the representation of rural-urban working population for the period between 1991-2011

5. Conclusions

This study used a machine learning-based multi-temporal remotely sensed image processing framework to show how the urban development of Rajarhat-Newtown occurred over time in the context of land use land cover changes and to discriminate between transient and spatial improvement plans using the Google Earth Engine platform. As a result of the varied character of developed metropolitan zones, satellite image preparation in an urban setting is presented with some unique challenges. The results demonstrated how a streamlined land cover guide might be supplied straightforwardly. The best assessment for investigating urbanization in peri-urban areas and urbanization patterns is that hard-core planners frequently express feelings according to specified plans. Besides, regional peri-urban hinterlands and regions are governed as zones that should be best planned and developed to meet the city's immediate needs and passion. Therefore, policymakers must emphasize a coordinated effort that benefits both the city centre and the non-urban perimeter. By focusing on a specific segment of fringe change, researchers were able to look into the more conspicuous measurements of dispute and upheaval, strain, and turbulence in the relationship between a city and its peri-urban and provincial interfaces. The research attempted to centre around integrated and general spatial advancement as important mainstays of profitable urbanization by exposing insight into various social and biological issues of change to urban areas.

Statements and Declarations

Data Availability Statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Conflicts of Interest

The authors declare no competing interests.

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