Chapter 16
Assessment of LULC Changes and Its Impact on Agricultural Landscape in Peri-urban Space of Bolpur Town, West Bengal (India)

Sanu Dolui and Sumana Sarkar

Abstract As the cityscape of large metropolitan cities gets increasingly supersaturated, policymakers and developers are being compelled to transform undeveloped land and the natural landscape of peri-urban areas into urban fabrics. Industrial developers and entrepreneurs' first choice was the peri-urban spaces where land is readily available for construction without a hassle of complicated legal restrictions; furthermore, government's supportive policies on infrastructure development may have exacerbated the impacts of urbanisation on the ecological and agricultural areas. After the beginning of the economic liberalisation and more import friendly policies in the early 1990s resulted in massive socioeconomic growth and infrastructure developments untimely led urban land use spread out of the city into the peri-urban area along the major highways. Therefore, this study aimed at quantifying and evaluating the trends of urban growth and how it affects farmland in the peri-urban areas of Bolpur town using an integrated approach of GIS tool and support vector machine (SVM) learning algorithms. Comprehensive LULC maps were generated for four distinct years during a 30-year span using a multi-temporal (1990–2020) Landsat dataset, following that, classified images were validated with actual G.P.S data. Kappa statistics indicate a satisfactory result with more than 86% accuracy for all those images. Observations derived from present study reveal that over the past 30 years a significant change occurred in the LULC; a major portion of agricultural land and forested area was converted into a residential area for developing tourism and township projects.

Keywords Peri-urban · GIS · Landsat dataset · LULC change · Kappa statistics · SVM algorithms

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Introduction

Land has always been crucial to sustain life on earth as well as the advancement of human civilisation. Alteration in LULC is acknowledged as a basic contributor to climatic change and biodiversity loss, and it has been one of the most pressing concerns in the contemporary decade that is predicted to be continue in future also (Mustard et al. 2012; Li et al. 2013). Only a few landscapes remained on the planet that has not been impacted by human activities, either located in remote locations or in exceedingly difficult terrain (Ritchie and Roser 2021). Urbanisation has become a universal phenomenon; an emerging problem particularly for developing nations experiencing a staggering increase in the proportion of people that resides in urban areas. This bewilderingly expansive process of disorderly growth is unpredictable, often leading to profligate and disastrous patterns of urban development (Travisi and Camagni 2005). Peri-urban expansion is very common pheno menon in Indian cities, where rural and urban traits tend to overlap on the outskirts and urban areas are substantially advancing towards adjacent rural places. A multitude of effects have been resulted from peri-urbanisation, including habitat destruction, ecological degradation, obliteration of agriculturally productive lands, as well as the transformation of desolate and natural vegetation lands into human-built landscapes (Afriyie et al. 2013; Seifollahi-Aghmiuni et al. 2022). Increased anthropogenic activities resulting from population growth have triggered speedy alteration of LULC. However, these consequences are most severe for those people who belong to economically disadvantaged group and totally reliant on the agriculture and forest for their livelihood (Acheampong et al. 2022). This trend will necessitate in the spatial expansion of urban centres outside respective administrative boundaries into their rural outskirts in order to make way for the expanding population in respective cities (Mosammam et al. 2016). Peri-urban land use change issues have recently attracted the attentions of academics who are interested in gaining a deeper comprehension about the causes and environmental repercussion of LULC change**.** As a consequence, monitoring of LULC changes is inexorably intertwined to continue human wellbeing and development projects, particularly in peri-urban areas where LULC changes have been exacerbated by due unplanned population growth (Wilson and Chakraborty et al. 2013; Mundia and Aniya 2005;keshtkar et al. 2017).

During the recent decades, most of the medium-sized Indian cities have experienced extraordinary spatial growth of urban land usage in peri-urban spaces, unfolding in a fragmentated, chaotic, distorted fashion (Feola et al. 2019; Follmann et al. 2018). Future commercial and residential townships, green infrastructure, new towns development, planned city expansions, infrastructure upgrades and transit corridors all represent this peri-urban reality, posing new challenges to urban administration and ecological sustainability (Mortoja et al. 2020). As a result, peri-urban areas are expected to grow endlessly, possibly even faster than large urban areas in the near future. Peri-urbanisation has increased the demand for land, thus triggering landscape modification and increasing the likelihood of land fragmentation (Appiah et al. 2015; Dutta 2012; Shaw and Das 2018; Ghosh et al. 2018). A number of researches had been carried out on peri-urban LULC changes, as well as the implications of these changes on farmland natural vegetation cover (Appeaning Addo 2010; Otunga et al. 2014; Alam et al. 2019; Ayele and Tarekegn 2020). The growth of cities has led to a reduction in the amount of land that is suitable for agricultural use, it has had a disastrous effect on farmers in the peri-urban areas, leaving relatively few croplands available for farmers. Further expansion of urban fabric onto arable land, have a harmful impact on the size, intensity, productivity, and profitability of that land (Atu et al. 2012; Sankhala and Singh 2014). Large tracts of valuable farmland are frequently sacrificed to make way for the expansion of urban infrastructure and the development of new townships (Fazal 2000). Agricultural landowners in peri-urban areas are primarily motivated by maximising profits as land value increases; as a result, they ignore the ecological consequences of their decisions (Adelaja et al. 2011). While some studies have found beneficial results from the conversion of agricultural land that had a positive effect on the economy of the surrounding area because it has made local communities more accessible to new employment opportunities (Wang and Qiu 2017). It has been observed that there are no stringent regulations regarding the encroachment of unplanned housing on agricultural land (Ayele and Tarekegn 2020). In most circumstances, there may be restrictions that are intended to limit these conversions, but local politicians and real-estate agents frequently avoid these regulations. As a consequence, agricultural land, which is the primary source of livelihoods for the majority of people in the country, is declining day by day.

Land use denotes to how humans utilise (anthropogenic utilisation) the biophysical components of land, whereas land cover denotes geophysical and ecological landscape which covers the earth land surface (Islam et al. 2018). It is vital to have a solid understanding of the dynamics, amplitudes and rates of LULCC change in order to generate helpful information for the development professionals and governments (Padmanaban et al. 2017). Notably, remote sensing technique and geospatial approaches have been demonstrated as a valuable and efficient method of LULC monitoring which investigated the modification of urban landscapes in a scientific and repetitive manner (Liu et al. 2005). A significant amount of study had been conducted over the past three decades in the topic of detecting urban land changes using remotely sensed imagery (Sun et al. 2020; Hegazy and Kaloop 2015; Dutta et al. 2015). Numerous studies reported that LULC classification with low- and mid-resolution images have a number of spectral and spatial deficiency which negatively affect classification accuracy (Akar and Gormus 2021). Consequently, academics have been employing machine learning algorithms in an effort to reduce the constraints of medium- and low-resolution images previously mentioned and in order to produce high-precision LULC images. In recent times, machine learning algorithms purposefully utilised for LULC mapping of remotely sensed images have gained a significant amount of attention among researchers (Jamali 2019; Abdi 2019; Talukdar et al. 2020; Roy 2021). This domain is rapidly evolving, and new algorithms and applications are constantly being developed. One of the machine learning algorithms that have been used most frequently is support vector machine (SVM) construct the best separating of hyperplane based on optimal demarcation line between two different classes. SVM algorithms are basically a novel machine learning algorithm which proved their effectiveness by demonstrating their durability in pattern recognition in mapping extremely heterogeneous urban landscapes over other conventional classifiers though the remote sensing domain has not yet fully embraced (Shi and Yang 2015). SVM the performance of SVM algorithms has been superior to that of other classifiers due to their excellent ability to generalise complicated attributes (Shao and Lunetta 2012; Lefulebe et al. 2022; Abbas and Jaber 2020; Rana and Venkata Suryanarayana 2020).

In the present study, Bolpur basically a university-centric town with several popular tourist spots in Birbhum District has been selected. This town had experienced rapid changes over the last three decades due to tourism, township and industrial development, and these new developments are mostly taking place at the expense productive agricultural land. To be more specific, the following objectives will be accomplished through the course of research (i) To capture the spatio-temporal pattern of LULC for four different years, viz. 1990, 2000, 2010 and 2020 using Landsat images, (ii) to demonstrate the direction, nature, rates and dynamism of changing landscape and (iii) Change detection and accuracy assessments of the produced output, i.e. classified images.

About Study Areas

Bolpur town and its surrounding fringe areas were located in the southernmost part of West Bengal's Birbhum District, roughly extended from 87° 35″ E to 87° 48″ E to 23° 35″ N to 23° 47″ N.

This area is a part of the ancient ***Rarh*** region in the lower Ganga track, geologically a flat terrain with a slight undulating topography with an altitude ranges from 46 to 62 m. The present study area Bolpur City situated at the confluence of the ***Mayurakshi*** and **Ajay rivers** and encompassing by rich agricultural rural hinterland. New townships and industrial estates constructed on rural landscapes as a result of peri-urban expansion lead the existing cropland and forest landscape to be fragmented and which has ramifications for ecological, socioeconomic and urban governance. Bolpur being a popular tourist destination in West Bengal, a decent number of tourists are visiting in this town all through the years to facilitate them, and a number of tourist hotels and resorts as well as government housing units were developed at the edge of the city, keeping in view the tourism potentiality of this town. In this context, therefore, this study sought to determine thirty-year past land use and land cover trajectory, as well as its repercussions on greenery in Bolpur and its peripheral settlement (Fig. 16.1).

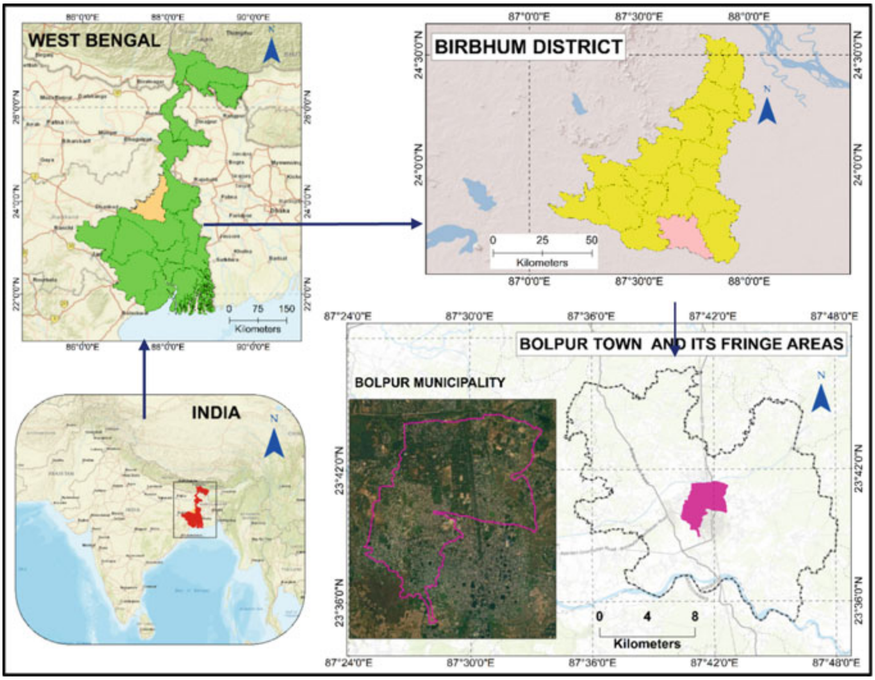

Fig. 16.1 Location map of Bolpur City and its surroundings

Methodology

Spatial Data

In this study, three different sets of Landsat TM images and one set of Landsat 8 OLI images were (path/row 139/44) retrieve from the USGS website (https://earthexplorer.usgs.gov). In order to improve the visualisation and interpretation of the images, a 15-m panchromatic band of Landsat 8 was fused with multispectral bands of 30-m resolution**.** For the evaluation and quantification of the spatial and temporal dynamics of the LULC, historical and contemporary Landsat satellite images for the years 1990 (date: 1990-10-20), 2000 (date: 2000-10-31), 2010 (date: 2010-11-12) and 2020 (2020-11-07) were used for the study. The images were taken for the similar month in different years as well as based on availability and less than 10% cloud cover to minimise the effects of seasonal changes as well as impact of and changing position of sun. Pre-processing of satellite images was required because differences between the two dates caused by atmospheric or sensor oscillations needed to be reduced or eliminated. For this reason, atmospheric, geometric and radiometric corrections were performed on the images as part of the pre-processing step. The FLAASH®

Table 16.1 Details of Landsat images data used for the analysis of land use and land cover (LULC) in the study area

Town name	Satellite	Acquisition date	Resolution (m)	User band	Sensor	Row/Path	Sources
Bolpur	Landsat 5	1990-10-20	30	1-5,7	Thematic mapper	Path: 139 Row: 44	USGS
		2000-10-31	30	1-5,7			USGS
		2010-11-12	30	1-5,7			USGS
	Landsat 8	2020-11-07	30.15	1-7,8,9	Operational land imager (OLI)		USGS

model technique was employed in this study for the purpose of addressing particularly taxing atmospheric conditions, such as the presence of clouds and surface reflectance. For the purpose of geometric registration, the 2020 image was georeferenced utilising G.P.S. points and registered with the standard Universal Transverse Mercator (UTM) 45 N zone. Prior to performing the supervised classification, a classification scheme was developed on the basis of supportive evidences (Table 16.2), field study, experience of local dwellers and visual assessments of each LULC class was verified through Google Street View imagery. Hybrid SVM classifier employed in order to extract LULC information as several researchers have popularly used this SVMs algorithm to separate LULC features robustly (Guo and Boukir 2015; Huang et al. 2007; Nooni et al. 2014) (Table 16.1; Fig. 16.2).

Adaptation of Classification Scheme

A classification approach was devised for the purpose of this study after Anderson et al. (1976) and the Food and Agriculture Organization (Di Gregorio and Jansen 2000) classification scheme as well as information from earlier investigations for the identification of the prevalent LULC classes. In addition, informations are gathered from the different stakeholders such as farmers, property dealers and local inhabitants in order to verify data derived from satellite images, and to explore the reasons, type of changes in the land use and land cover pattern and its impacts, in and around Bolpur City. Different LU/LC types and their basis of classification employed in this study are outlined below (Table 16.2).

Table 16.2 Description of land use/land cover (LULC) classes

Serial number	Land use/Land cover types	Item included	Description
1	Built-up areas	Mainly including residential, commercial centers, industrial zones, railways, highways, expressways and others, rural settlements	Built-up the land type is distinguished by extensive land use, where anthropogenic activities have changed the landscape
2	Agricultural land	All cultivated and uncultivated arable land areas, such as croplands, irrigated paddy fields, potatoes cropland, and grazing land, among other types of agricultural land	The grounds that are classed as agricultural lands are those that have a few scattered communities surrounded by agricultural lands
3	Forest and reserved forest	Area include national forest, sanctuaries, reserved forest protected forests, deciduous forest, mixed forest lands	A reserved forest (also called protected forest) or protected forest denoting forests accorded a certain degree of protection
4	River and canal	The streams and canals category includes major and minor river and canals permanent and seasonal	This is a natural course of water following a linear contiguous pattern that have a minimum width of 80 feet
5	Water bodies	Open water, lakes, ponds, and various reservoirs	Reservoirs, naturally occurring lakes, and other types of water bodies that are not open to the flow of water are examples of water bodies that are non-flowing and naturally enclosed
6	Barren land/Bare soil	Exposed and bare soils included in this category are open spaces, places with exposed soils, landfills, fallow land, earth and sand land in-fillings, and land that has not been planted with vegetation	In a context that is not urban, barren areas are characterised by thin soil, sand, or rocks, as well as an absence of vegetation cover. If vegetation is present, it is dispersed extensively

LULC Classification Based on Support Vectors Machine Learning Algorithms

In recent years, there has been an effort to develop more trustworthy and efficient classification algorithm. Support vector machines are one of the most prevalent and

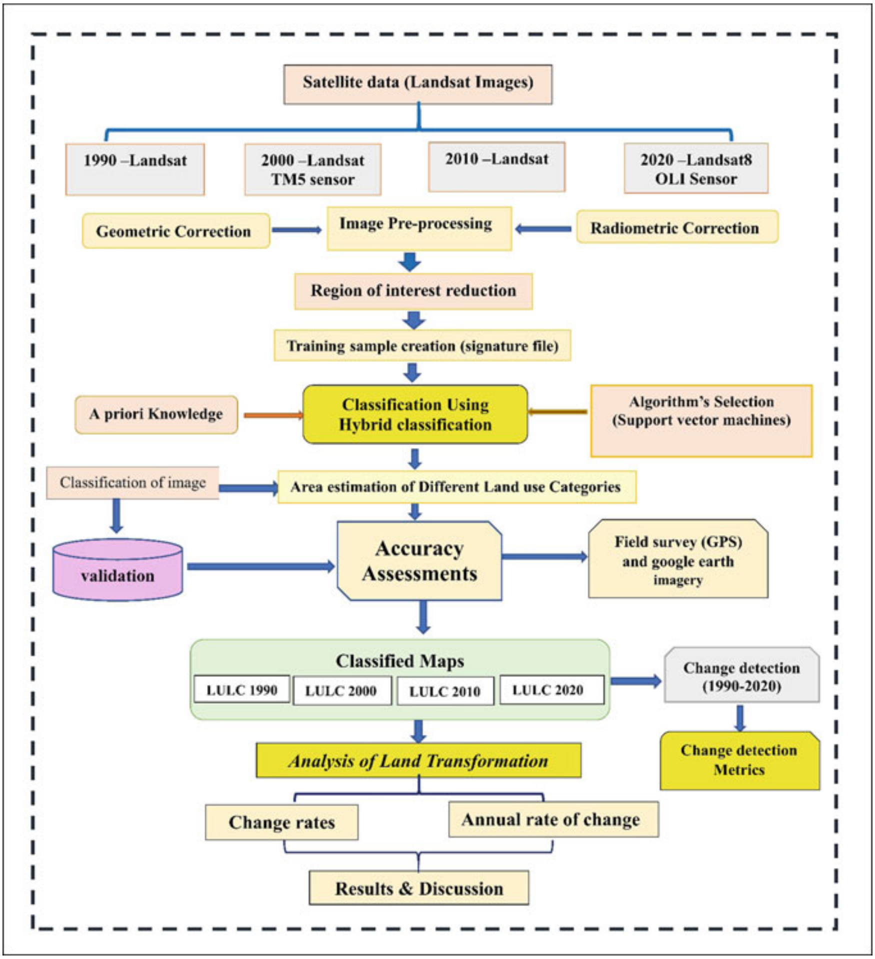

Fig. 16.2 Methodology of the study

recommended machine learning algorithms based on the principle to build an optimal decision boundary (a separating hyperplane) to separate (or classify) the data for different classes (Mountrakis et al. 2011). Nonparametric classifiers like SVMs that do not reliant on any preconceptions from the dataset and also have the potential to overcome the restrictions that are associated with parametric classifiers (Kavzoglu and Colkesen 2009; Ustuner et al. 2015; Pal 2012). Existing literature on the detection of LULC changes reveals that support vector machines learning algorithms are the most stable and frequently used algorithms successfully classified LULC with high accuracy, that is why in the present study SVM classification has been used to classify the Landsat images of Bolpur for the year 1990, 2000,2010 and 2020 (Fig. 16.3).

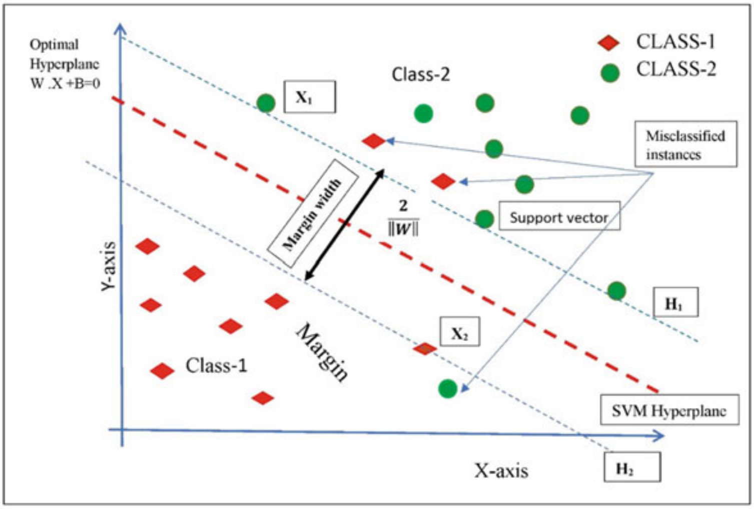

Fig. 16.3 Support vector machines—examples of optimal decision boundaries

Accuracy Assessment

A crucial stage in LULC change analysis is the assessment of an image's accuracy due to the uncertainty in the selection of the training and reference samples (Congalton 1991). Cohen's kappa coefficient (K) is a powerful statistical tool for assessing the agreement between anticipated and observed categorisations of a dataset. If the accuracy of a classified images is more than 75%, overall accuracy is considered as adequate (Tilahun 2015). For evaluation of the overall accuracy, kappa statistics, producer's and user's accuracy were used. An evaluation of the accuracy of the LULC change analysis was carried out by constructing a confusion/error matrix in each LULC. For the 2020 image, 247 GPS points acquired using Garmin G.P.S (eTrex-30), purposefully to ensure sufficient representation of each LULC types. For rest of year, 200 reference points were generated for the years 2010, 2000 and 1990 as reference samples over the study area for the individual Landsat images. The equation suggested by Jensen and Cowen (1999) was utilised in the computation of the Kappa coefficient. Kappa coefficients typically lie between 0 and 1, if the value of the kappa coefficient is less than 0.4, the level of agreement is considered to be weak; if the value is between 0.4 and 0.8, the level of agreement is considered to be moderate; and if the value is larger than 0.8, the level of agreement is considered to be strong. Kappa coefficient was determined by using equation (Table 16.3).

Table 16.3 Algorithms for accuracy assessment

Overall accuracy (OA)	$\frac{\text{Total number of correctly classified pixel(diagonal)}}{\text{Total number of Reference pixel}} \times 100$
User accuracy (UA)	$\frac{\text{Number of correctly classified pixel in each categories}}{\text{Total number of classified pixel in that categories(row total)}} \times 100$
Producer accuracy (PA)	$\frac{\text{Number of correctly classified pixel in each categories}}{\text{Total number of classified pixel in that categories(Column total)}} \times 100$
Kappa coefficient (T)	$\frac{(\text{Total sample} \times \text{Total corrected sample}) - \Sigma(\text{Column total} \times \text{row total})}{\text{Total sample}^2 - \Sigma(\text{Column} \times \text{row total})}$
Commission error	$\frac{\sum \text{Off Diagonal element of Row}}{\text{Row Total}} \times 100$
Omission error	$\frac{\sum \text{Off Diagonal element of Column}}{\text{Column Total}} \times 100$

Analysis of Urban Expansion by Change Assessment

Land use change assessment is the process of detecting distinct land use patterns and phenomena through observing at multiple timeframe (Singh 1989). This analysis makes LULC research interesting since it not only investigates changes that have occurred but also determines their nature and trend. Techniques like GIS and remotely sensed satellite database have now been extensively employed to determine changes in LULC, especially urban growth (Das and Angadi 2021) and cropland transformation (Mazumder et al. 2021). The following equations have been used to track changes in LULC throughout the mentioned timeframe (1990–2020).

$$\text{Decadal LULC Gain/Loss} = \text{Final LULC Area} - \text{Initial LULC Area} \quad (16.1)$$

$$\text{LULC Gain/Loss(in \%)} = \frac{(\text{Final LULC Area} - \text{Initial LULC Area})}{\text{Initial LULC Area}} * 100 \quad (16.2)$$

The Urban Expansion Index (UEI) which was introduced with the purposes of quantification of urban expansion was calculated for the periods: 1990–2000, 2000–2010, 2010–2020 and 1990–2020 using equations below:

$$\text{UEI} = \frac{\text{UL}_{T_2} - \text{UL}_{T_1}}{n \times \text{TA}} \quad (16.3)$$

where UL represents urban land; T_2 denotes succeeding year; T_1 represents initial years; time gap between T_2 and T_1, in years; and TA represents total area of the landscape.

Results and Discussion

Land Cover Maps and Status

The surrounding peri-urban villages of Bolpur with substantial land resource potential have become an appealing location desired by young inhabitants and property dealers for accommodation and business developments. SVM algorithms were adopted for the purpose of performing supervised classification on Landsat images (TM and OLI/TIRS) for the years 1990, 2000, 2010 and 2020 to quantify the urban expansion of Bolpur City over the past 30 years. Major six land use land cover types were identified and extracted to prepare four classification maps for Bolpur town and its surroundings. These were categorised as follows: (a) agricultural land, (b) built-up areas, (c) forest areas, (d) barren/exposed soil, (e) river and canal and (f) water bodies (Fig. 16.4).

Land Use and Land Cover (LULC) Change

Here in this following section, a summary of the results for each LULC class and their fluctuation of changes underwent discussed separately. Observation can be drawn that due to the attractive natural landscape and spectacular village ambience surrounded by forest and agricultural land, and there have been decent amounts of agricultural land converted into residential apartments and eco-tourism resorts in the study area. As a result, other urban development activities based on tourism activities have been observed throughout the study area. Changes in land use in each category are discussed separately as LULC information derived from multi-temporal Landsat images by an SVM–supervised classifier (Fig. 16.5).

The sprawling of built-up areas: Bolpur City has experienced astonishing and chaotic urban growth over the past 30 years as a direct consequence of an increase in population. Agricultural land fragmentation can be witnessed from satellite images and ground-based observations. The amount of built-up land in 1990 was 28.93 km^2 accounting only (10.03%) of the total area, while in year 2000 (12.41%) and in 2010 (17.10%) and finally in 2020 (24.49%) area cover with built-up land, it can be noticed a substantial rise in built-up area with 132.32% increase in last three decades (Tables 16.4 and 16.5).

Change in agricultural area: Percentage of agricultural area steadily decrease from 1990s 198.30 (68.73%) km^2 to 2020 159.92 (55.43%) km^2. Initially, the positioning of the agricultural land in the vicinity of Bolpur City, as well as the increasing rates of urbanisation in the area and the presence of a large number of agro-based industries and industrial estates, were the primary reasons for the drop in agricultural land.

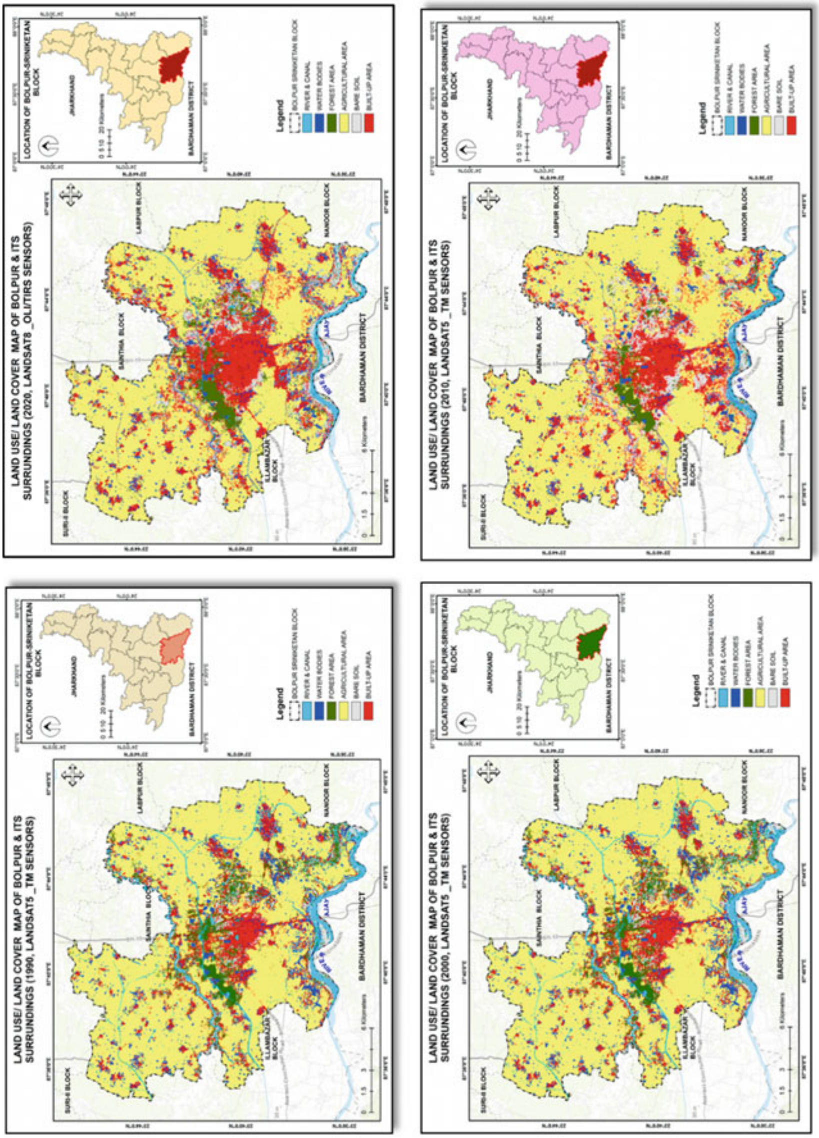

Fig. 16.4 Land use and land cover map of Bolpur town for the year (1990, 2000, 2010 and 2020) (compiled by the author)

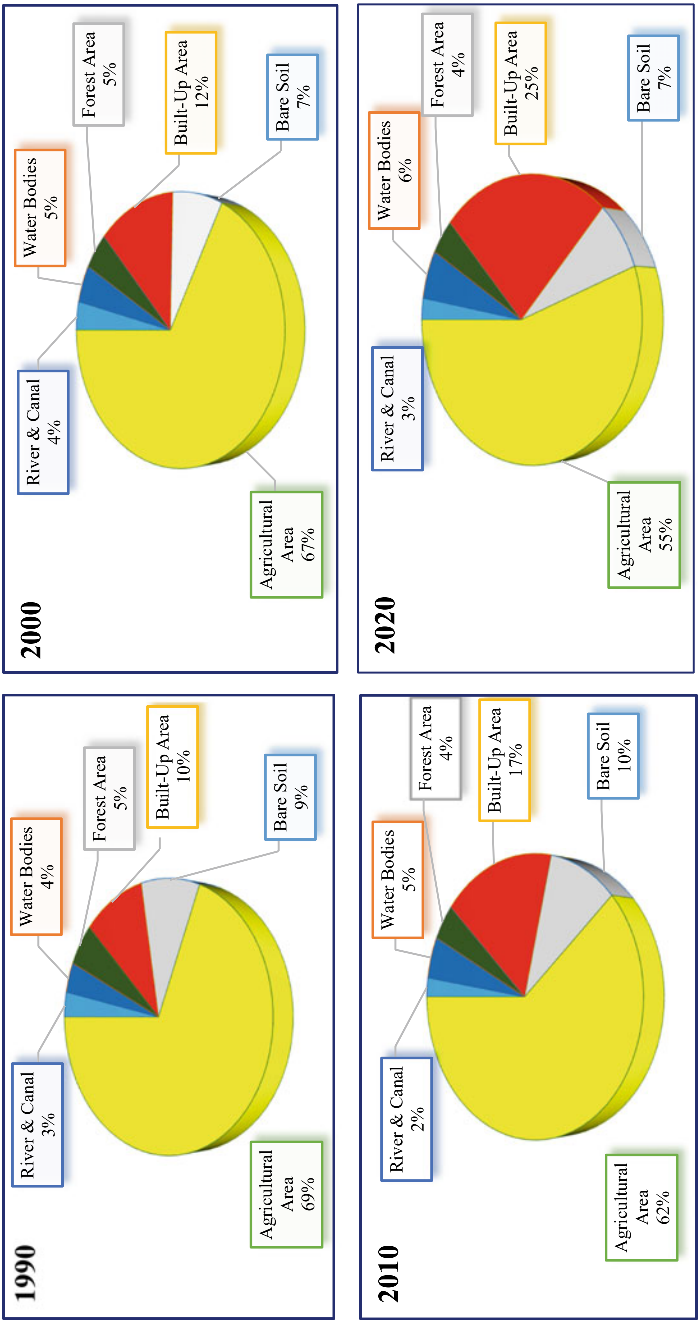

Fig. 16.5 Proportion of different types of LULC in different years of Bolpur town (1990–2020)

Table 16.4 Comparison of areas based on the six LULC classes and annual rate of change between (1990–2000), (2000–2010), (2010–2020), (1990–2020) of Bolpur town and its fringe areas

Land use classes	Year 1990		Year 2000		Year 2010		Year 2020		Change between 1990 and 2000 ($T_2 - T_1$)		Annual rate of change	
	Area in km^2	(%) LU/LC	Area in km^2	(%) LU/LC	Area in km^2	(%) LU/LC	Area in km^2	(%) LU/LC	Area in km^2	(%) LU/LC from initial	Per year km^2	(%) of change
River and canal	9.14	3.17%	10.53	3.65%	6.75	2.34%	7.53	2.61%	1.39	15.26	0.14	1.53
Water bodies	11.01	3.82%	13.56	4.70%	14.62	5.07%	17.02	5.90%	2.55	23.19	0.26	2.32
Forest area	15.18	5.26%	13.24	4.59%	12.67	4.39%	12.14	4.21%	−1.94	−12.78	−0.19	−1.28
Built-up area	**28.93**	**10.03%**	**35.81**	**12.41%**	**49.33**	**17.10%**	**70.66**	**24.49%**	**6.87**	**23.76**	**0.69**	**2.38**
Bare/Exposed soil	25.94	8.99%	21.74	7.54%	27.88	9.66%	21.23	7.36%	−4.20	−16.20	−0.42	−1.62
Agricultural area	198.30	68.73%	193.62	67.11%	177.25	61.44%	159.92	55.43%	−4.68	−2.36	−0.47	−0.24
SUM	288.50		288.50		288.50		288.50					

Land use classes	Change between 2000 and 2010 ($T_3 - T_2$)		Annual rate of change		Change between 2010 and 2020 ($T_4 - T_3$)		Annual rate of change		Change between 1990 and 2020 ($T_4 - T_1$)		Annual rate of change	
	Area in km^2	Percentage of change	Area in km^2	Percentage of change	Area in km^2	Percentage of change	Area in km^2	Percentage of change	Area in km^2	Percentage of change	Area in km^2	Percentage of change
River and canal	−3.79	−35.94	−0.38	−3.59	0.78	11.62	0.08	1.16	−1.61	−17.59	−0.05	−0.59
Water bodies	1.06	7.80	0.11	0.78	2.40	16.42	0.24	1.64	6.01	54.60	0.20	1.82
Forest area	−0.57	−4.31	−0.06	−0.43	−0.53	−4.18	−0.05	−0.42	−3.04	−20.03	−0.10	−0.67

(continued)

Table 16.4 (continued)

Land use classes	Change between 2000 and 2010 ($T_3 - T_2$)		Annual rate of change		Change between 2010 and 2020 ($T_4 - T_3$)		Annual rate of change		Change between 1990 and 2020 ($T_4 - T_1$)		Annual rate of change	
	Area in km^2	Percentage of change	Area in km^2	Percentage of change	Area in km^2	Percentage of change	Area in km^2	Percentage of change	Area in km^2	Percentage of change	Area in km^2	Percentage of change
Built-up area	**13.53**	**37.79**	**1.35**	**3.78**	**21.33**	**43.24**	**2.13**	**4.32**	**41.73**	**144.25**	**1.39**	**4.81**
Bare/Exposed soil	6.14	28.24	0.61	2.82	−6.65	−23.85	−0.67	−2.39	−4.71	−18.16	−0.16	−0.60
Agricultural area	−16.37	−8.46	−1.64	−0.85	−17.33	−9.78	−1.73	−0.98	−38.38	−19.36	−1.28	−0.64

Source Computed by researcher

Table 16.5 Trend of urbanisation in Bolpur (expansion of built-up land)

Land use classes	1990	2020	Change between 1990 and 2020		Annual rate of change	
	Area in km^2	Area in km^2	Area in km^2	Percentage of initial	UEAR = $U_1 - U_2/T_1 - T_2$ (km^2)	Percentage
Built-up area	28.93	70.66	41.73	144.25	1.39	4.81

Changes in river areas: Nothing significant has changed within this 30-year time span in river course through LULC monitoring; however, there are certain areas where the river banks are showing evidence of having dried up. In **Ajay River**, there was a shift in river channel during the late quaternary era; numerous paleochannels, oxbow lakes and elongated sediment fills are observed there (Roy and Sahu 2016), and those remnants of paleochannels are exploited for agricultural and residential purposes. Mainly differentiation in areas of river bed occurs due to seasonal variation of water and excessive sedimentation. In 1990, the area under the river channel was 09.14 km^2; in the year 2000, it was 10.53 km^2; after that in 2010, it was 6.75 km^2, and finally in 2020, area under river course is 07.53 km^2.

Area under exposed/bare soil: The majority of the barren or exposed soil is laterites deposition in forest areas, as well as those exposed soil located in eastern parts of Bolpur town; subsequently, industries and other economic activities have been developed on those places. There is a marked decline in exposed soil over these time periods. The area under exposed soil has decreased from 25.94 km^2 in 1990 to 21.23 km^2 in 2020, a decrease of (−19.35%) in the last 30 years.

Increase in water bodies: As the population of surrounding village increases, therefore, demand for freshwater for household and other activities increases which illustrates why the area under water bodies has grown on a regular basis. Between 1990 and 2020, the area covered by water bodies increased from 11.01 km^2 in 1990 to 17.02 km^2 in 2020, a 54.59% increase in the proportion of water bodies throughout this time period.

Forest area decreases in slower space: A small patch of forest cover along the **Amar Kuthir** Road areas, including ***Ballavpur Wildlife Sanctuary & Sonajhuri*** Forest, located a bit away from Main Bolpur town. Over the course of the past thirty years, there has not been a notable shift in the forest cover. In 1990, the area covered by forest cover was 15.18 km^2, and by 2020, the area covered by forest was approximately 12.18 km^2 representing a drop-in forest cover of approximately −20.02% during 30 years (Fig. 16.5).

Land Use and Land Cover (LULC) Change Detection

The LULC change matrix (Tables 16.4 and 16.5) demonstrates that the distribution of primary transitions in each of the six (6) LULC categories differed between 1990 and 2000, 2000 and 2010, 2010 and 2020, and 1990 and 2020, respectively. According to the findings of the study, there were significant shifts and transitions among the six LULC groups.

The analysis of the classified image of **1990 reveals** that agricultural land accounted for approximately 68.73% (198.30 km^2) of the total land area which demonstrates the widespread involvement of people in agricultural activities as well as the predominance of the agro-based economy. Whereas built-up area, the second most prevalent land cover, accounted for 10.03% (28.93 km^2) of the total land, bare soil accounting for 8.99% (25.94 km^2, forest and protected areas occupied 5.26% (15.18 km^2), respectively, waterbodies accounting for almost 3.82% (11.01 km^2), and the remaining 3.17% (9.14 km^2) areas of the total geographical area are occupied by river and canal.

Moreover from the **classified images 2000**, agricultural land accounted for approximately 67.11% (193.62 km^2) indicating slightly decreases (− 4.68 km^2) from the previous year 1990, whereas built-up area accounting for 12.41% (35.81 km^2) of the total land areas, bare soil accounting for 7.54% (21.74 km^2), forest and protected areas occupied 4.59% (13.24 km^2), respectively, waterbodies accounting for almost 3.82% (13.56 km^2), and the remaining 3.65% (10.53 km^2) areas of the total geographical area are occupied by river and canal.

The assessment of classification results **from 2010 discloses** that, agricultural land was still remains main land cover, accounting for approximately 61.44% (177.25 km^2) of the total land area, whereas the second most important land use type is a built-up area, accounting for 17.10% (49.33 km^2) which indicating drastic increases from the year 2000 (12.41%), bare soil accounting for 9.66% (27.88 km^2), forest and protected areas occupied 4.39% (12.67 km^2), respectively, waterbodies accounting for almost 5.07% (14.62 km^2), and the remaining 2.34% (6.75 km^2) areas of the total geographical area are occupied by river and canal.

The observation of SVM classifier **from 2020 demonstrates that**, agricultural land was the dominant land cover accounting for nearly 55.43% (159.92 km^2) of the total land area, while built-up area accounted for 24.49% (70.66 km^2) revealing substantial increases from the year 2010, bare soil accounting for 7.36% (21.23 km^2), forest and protected areas occupied 4.21% (12.14 km^2), respectively, waterbodies accounting for almost 5.90% (17.02 km^2), and the remaining 2.61% (7.53 km^2) areas of total geographical area are occupied by river and canal (Fig. 16.6; Table 16.6).

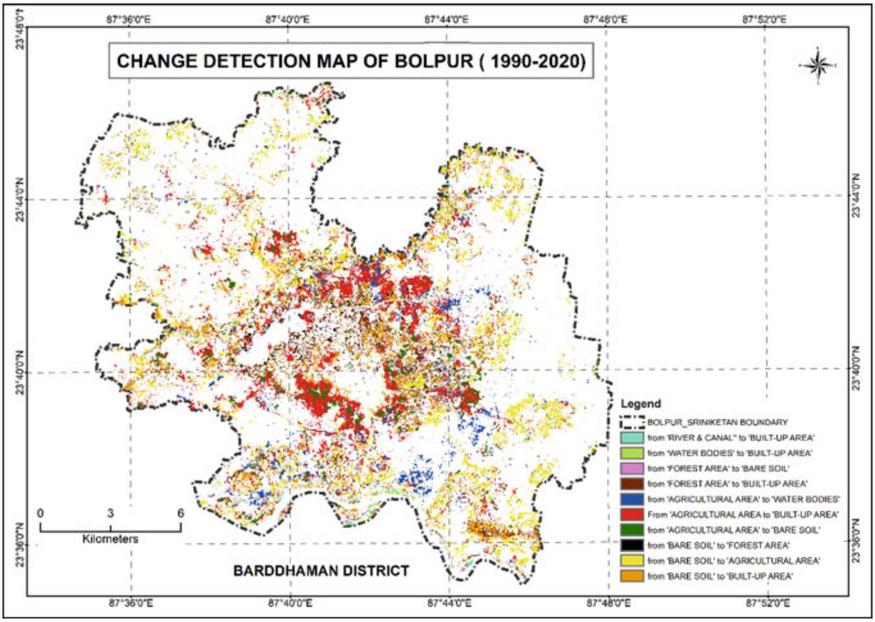

Fig. 16.6 Change detection map of Bolpur town

Table 16.6 Computation of change detection matrix between 1990 and 2020 for Bolpur town

Final state 2020 (km^2)	Land use types	Initial state-1990 (km^2)						
		River and canal	Water bodies	Forest area	Agricultural area	Bare/Exposed soil	Built-up area	Row total
	River and canal	**6.43**	1.39	0.34	0.79	1.13	0.57	**10.65**
	Water bodies	0.48	**5.71**	0.53	4.48	3.73	2.87	**17.79**
	Forest area	0.09	0.59	**8.83**	1.61	1.20	1.48	**13.79**
	Agricultural area	0.29	2.19	3.27	**151.80**	1.11	1.03	**159.68**
	Bare/Exposed soil	1.23	0.68	1.31	3.11	**12.28**	3.35	**21.96**
	Built-up area	4.25	2.39	5.67	23.68	5.89	**23.75**	**65.63**
	Class total	**12.77**	**12.94**	**19.96**	**185.46**	**25.33**	**33.04**	**289.50**
	Class changes	6.34	7.23	11.12	33.66	13.05	9.29	0.00
	Image difference	− 2.121	4.854	− 6.164	− 25.780	− 3.372	32.584	0

Gain–Loss Analysis

Based on the results of SVMs classification, a change analysis process in LCM on IDRISI was used to obtain the data on land gain and loss as well as the net change for each LULC type for the period of 1990–2000 ($\boldsymbol{T_2 - T_1}$), 2000–2010 ($\boldsymbol{T_3 - T_2}$), 2010–2020 ($\boldsymbol{T_4 - T_3}$) and 1990–2020 ($\boldsymbol{T_4 - T_1}$), respectively. For the periods (1990–2020), Water bodies gaining 54.60% (11.01–17.02 km^2) while a significant gain was observed in built-up area which is about 144.25%, (28.93–70.66 km^2), on that same time the highest loss is recorded in the agricultural land decreasing 19.36% (198.30–158.92 km^2), followed by forest area decreases 20.03% (15.18–12.14 km^2), bare soil/barren land decreases 18.16% (25.94–21.23 km^2) and finally area under river and canal decreases 17.59% (9.14–7.53 km^2). In Bolpur town, the area under built-up area increased 41.73 km^2 during 1990–2020 years, and the agriculture area decreased around 38.38 km^2. Most of the agricultural land was converted to built-up land during this period. Other land uses like water bodies, forest area, river and canal have recorded minimum changes during this period (Fig. 16.7).

Agricultural Land Fragmentation

This town is known as the cultural hub of West Bengal influenced by Nobel laureate Rabindranath Tagore's ideology; peoples feels an emotional touch with this area making it a favourite destination for residential township development. Recently, governments projects on housing development (**Gitabitan Township**), Construction of Educational institution (**Biswa Bangla university**), Bolpur Industrial estate and Tourism Development have boasted the recent fast-spaced urbanisation process mainly in peri-urban areas. Spotting from satellite images it was proved that the majority of these projects were developed on fertile agricultural land, and arising issues like land fragmentation, irregular shape of agricultural land, increased land value, encroachment, and unscientific construction which undermines building regulations and standards are the major impact of peri-urbanisation on agricultural land. The real-estate agents and property dealer taken away vast portion of land with minimum land price and after the installation of basic amenities, the land was sold at extremely high prices, increasing the overall area valued of this agricultural land to a considerable extent. Besides that fragmentation of agricultural land makes cultivation less profitable on the other hand increased land value tempted the peri-urban farmer to sold their land which negatively affects the principle of sustainability. The consequences of widespread land expansion have resulted in an incursion of residential uses into an agriculturally dominated rural area that is not yet ready to accommodate urban growth. This peri-urban area actually falls under the rural jurisdiction area (Gram Panchayat) lack of manpower and economic feasibility and dispersed nature of residential space, installation of civic amenities and facilities, household waste collection is exceptionally difficult. For detecting urban expansion between 1990 and

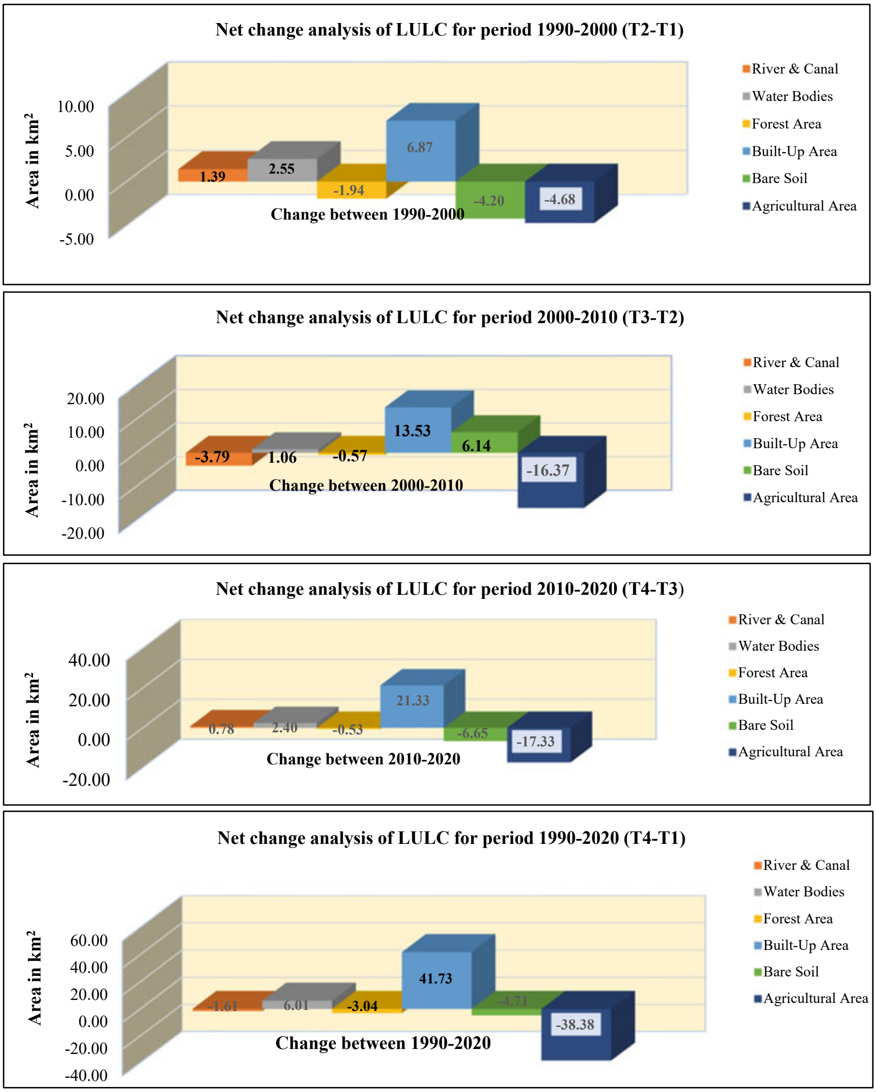

Fig. 16.7 Land gain and loss analysis for periods 1999–2000 ($T_1 - T_2$), 2000–2010 ($T_2 - T_3$), 2010–2020 ($T_3 - T_4$) and 1999–2020 ($T_1 - T_4$)

2020, the total built-up areas increased in that period was 41.43 km^2, with 1.39 km^2 annual increase, whereas within the same time frames agricultural areas decreased 1.18 km^2 per years, which is an alarming situation and a negative imputes of urbanisation. As most of land is privately owned government has lesser scope to intervene, on the other hand local inhabitant found that agricultural activities no longer profitable as the compared value of the land. Local farmers, particularly small-scale household

Fig. 16.8 Township development on agricultural land. *Source* Google Earth images (2020)

Fig. 16.9 Fragmentation of agricultural land. *Source* Google Earth images (2020)

farmers, feel that selling those lands to private developers would be a good deal in terms of securing their future (Figs. 16.8 and 16.9).

Accuracy Assessment of the Classification

When it comes to satellite image classification, the accuracy assessment will be the last step to take into consideration. As has been mentioned before, in order to validate the classification results, GPS points are gathered at randomly using a Garmin eTrex 30x GPS device for performing the accuracy assessment. The below confusion matrix table for 2020 describes that six different classes of LU/LC. In the year 2020 for accuracy assessment, 247 ground truth points were generated through personal field visit with GPS accuracy. For rest of the years (2010, 2000, 1990), 200 validation points were developed based on information of unchanged LULC cover through interviews with local residents and finally accuracy assessment points were verified with high-resolution Google Earth images**.**

Results of **user's accuracy** in this investigation revealed that in the year 2020, the maximum class accuracy was 96.61% for built-up area where correctly classified while the river and canal class had the lowest rate of accuracy at 82.00%, results are shown in (Tables 16.7 and 16.8). In 2010, the class accuracies range from 82.76 to 92.50% (Tables 16.9 and 16.10). In 2000, it ranges from 80.65 to 93.18% as indicated in Tables 16.11 and 16.12 whereas in the period 1990, the accuracy for different classes ranges from 80.65 to 97.67%, respectively (Tables 16.13 and 16.14).

Results of Producer's accuracy showed that in 2020 the maximum class accuracy near about 100% was found in river and canal area while the minimum was bare/exposed soil class with an accuracy of 73.91% as presented in Table 16.8. In 2010, the class accuracies range from 80.00 to 93.75%, whereas in the period 2000, it ranges from 82.14 to 92.59%. In the year 1990, the class accuracies range from 86.67 to 95.45%, as indicated in tables (Tables 16.10, 16.12 and 16.14), respectively.

Finally, **overall accuracy** for the year 2020 classification map was computed as 90.69% with overall kappa coefficient (T) value of 88.58%. During this year 2010, overall accuracy was 88.00%, with kappa coefficient (T) 85.38%, whereas in the period 2000, overall accuracy was 87.50% with kappa coefficient (T) 84.80%. Lastly, in the year 1990, the accuracies classes range from 82.14 to 90.24%, respectively; in this study period 1990, the overall accuracy was 90.50%, with kappa coefficient (T) value of 88.52% (Tables 16.8, 16.10, 16.12 and 16.14) The outcomes demonstrate that this classifier is capable of producing high classification accuracy and has a good level of agreement between ground truth and categorised data.

Discussion

Following the start of economic liberalisation and more pro-import policies in India in the early 1990s, which resulted in enormous socioeconomic growth and infrastructure advances, urban land use unpredictably led to the spread of the city into the peri-urban (Chadchan and Shankar 2012; Sarkar 2019). Being in a state of transition peri-urban spaces characterised by negligence, especially in underdeveloped countries. Owing to the fact that it was neither entirely urban nor entirely rural, and therefore, it does not fall under the jurisdiction of the authorities on either side. Nevertheless, it continues to accommodate the population that overflows from the surrounding urban areas despite the fact that it does not have the requisite infrastructure support. Up-to-date knowledge on urban landscape modification and its consequence on peri-urban greenery are utmost important to gaining our comprehension of the nexus between urban expansion and land use/cover change which may effective for environmental decision-making in peri-urban areas. A substantial portion of **Santiniketan** and the nearby **Prantik Station** area eco-tourism resorts are

Table 16.7 Computation of confusion matrix SVM algorithm for accuracy assessment of LULC map 2020, Bolpur town

Classified data (image to be evaluated)	Reference data (ground truth data)								
	Land use categories	River and canal	Water bodies	Forest area	Agricultural area	Bare/Exposed soil	Built-up area	Total (user)	Commission error
	River and canal	**41**	4	0	0	4	1	**50**	0.180
	Water bodies	0	**32**	1	0	0	1	**34**	0.059
	Forest area	0	2	**25**	0	1	0	**28**	0.107
	Agricultural area	0	0	3	**53**	0	1	**57**	0.070
	Bare/Exposed soil	0	0	0	2	**17**	0	**19**	0.105
	Built-up area	0	0	1	0	1	**57**	**59**	0.034
	Total (producer)	**41**	**38**	**30**	**55**	**23**	**60**	**247**	
	Omission error	0.000	0.158	0.167	0.036	0.261	0.050		

Table 16.8 Comparison of the different accuracy parameter, overall accuracy and kappa coefficient (2020)

Land use categories	User accuracy calculation	Producer accuracy calculation	Overall accuracy	Kappa coefficient (T)
River and canal	82.00	100.00	90.69%	88.58%
Water bodies	94.12	84.21		
Forest area	89.29	83.33		
Agricultural area	92.98	96.36		
Bare/Exposed soil	89.47	73.91		
Built-up area	96.61	95.00		

sprouting in an unplanned manner. The findings of the study confirm that contemporary biophysical transformations in this urban area of Bolpur town, as well as the expectation of increased pressure on peripheral urban green spaces. Furthermore, a decent number of colleges, university, teacher training colleges, institutes of technology and academic institutions located in Bolpur have resulted in an influx of students from different parts of India. Recently, the construction or real-estate industry, the hospitality sector, and marketing have all been in great demand, and as a result, employment opportunities have increased. Census data also confirmed recent growth; Bolpur City had a population of 52,760 in 1991, but the present urban population (2011) is approximately 112,591 including Bolpur City and surrounding census towns (Census of India 2011).

The percentage area of each class in 1990 and 2020 showed that agricultural area had the largest share in 1990 representing 68.73% (198.30 km^2) of the total LULC categories assigned. This class faced a steady decrease, and it was reduced to 55.43% (159.92 km^2). Built-up area experienced the highest rise, increasing from 10.03% (28.93 km^2) in 1990 to 24.49% (70.66 km^2) in 2020. Despite the fact that these transformations are creating opportunity for locals, there are negative repercussions that are showing adversely on the ecosystem. According to census information, a sizeable quantity of ecological landscapes has been transformed into urban settings as a direct result of the explosive growth of the human population and migration. In this study, SVM algorithms produced overall good amount of accuracy for each year over 86% indicate that SVM successfully classified those images.

Conclusion

The study attempts to comprehend the expansion of urban fabric in the peri-urban areas of Bolpur town using multi-temporal Landsat imagery. Bolpur town witnessed significant LULC changes between 1990 and 2020, with a decrease in the forest, agricultural land and exposed soil surface categories. The validation output reveals, that

Table 16.9 Computation of confusion matrix SVM algorithm for accuracy assessment of LULC map of 2010, Bolpur town

Classified data (image to be evaluated)	Reference data (ground truth data)								
	Land use categories	River and canal	Water bodies	Forest area	Agricultural area	Bare/Exposed soil	Built-up area	Total (user)	Commission error
	River and canal	**30**	3	0	0	2	1	**36**	0.166
	Water bodies	2	**22**	1	0	0	1	**26**	0.153
	Forest area	0	2	**24**	2	1	0	**29**	0.103
	Agricultural area	0	0	3	**45**	0	1	**49**	0.081
	Bare/Exposed soil	0	0	0	2	**18**	0	**20**	0.100
	Built-up area	0	0	2	0	1	**37**	**40**	0.075
	Total (producer)	**32**	**27**	**30**	**49**	**22**	**40**	**200**	
	Omission error	0.062	0.185	0.200	0.081	0.181	0.075		

Table 16.10 Comparison of the different accuracy parameter, overall accuracy and kappa coefficient (2010)

Land use categories	User accuracy calculation	Producer accuracy calculation	Overall accuracy	Kappa coefficient (T)
River and canal	83.33	93.75	88.00%	85.38%
Water bodies	84.62	81.48		
Forest area	82.76	80.00		
Agricultural area	91.84	91.84		
Bare/Exposed soil	90.00	81.82		
Built-up area	92.50	92.50		

results of SVM algorithm with overall accuracy of 90.69% (2020), 88.00% (2010), 87.50% (2000), 90.50% (1990) and kappa coefficient of 0.88 (2020), 0.85 (2010), 0.84 (2000), 0.88 (1990) have achieved good level of accuracy. It has been suggested that this algorithm can be used as an optimal classifier for the extraction of land use maps due to the fact that it possesses a greater level of accuracy and a better level of consistency within the study area. This research highlighted the importance of remotely sensed data and SVM algorithms in determining and anticipating the transformation of peri-urban landscape. The SVM approach is recommended as one of the finest classifier algorithms for extracting the maps LULC; ideally, this study might be useful in tracking LULC alteration. This study is noteworthy since other cities have also witnessed similar phenomenon of urban development onto agricultural land in peri-urban settings (Beckers et al. 2020; Bonye et al. 2021). So, the outcomes may be helpful for planner and policymakers to handle land use problems of this city in a better way as most of Indian city are at verge of conversion from an agrarian economy to manufacturing and service-based activities in order to lessen the impact urbanisation on fertile land. Instead of haphazard arrangements of the building which create land fragmentation, compact housing development and planned townships should be encouraged to mitigate the impact of land fragmentation. In concluding remarks, agricultural land should be conserved from being transformed to other uses to maintain food production as much as feasible without jeopardising urban growth. Future research on peri-urban space prediction and surveillance using machine learning algorithms, particularly SVM, is recommended to address the uncertainties and detrimental effects of peri-urbanisation on LULC change.

Table 16.11 Computation of confusion matrix SVM algorithm for accuracy assessment of LULC map of 2000, Bolpur town

Classified data (image to be evaluated)	Reference data (ground truth data)								
	Land use categories	River and canal	Water bodies	Forest area	Agricultural area	Bare/Exposed soil	Built-up area	Total (user)	Commission error
	River and canal	**25**	3	0	0	2	1	**31**	0.193
	Water bodies	2	**25**	1	0	0	2	**30**	0.166
	Forest area	0	2	**23**	2	1	0	**28**	0.178
	Agricultural area	0	0	2	**41**	0	2	**45**	0.089
	Bare/Exposed soil	0	0	0	2	**20**	0	**22**	0.090
	Built-up area	0	0	2	0	1	**41**	**44**	0.068
	Total (producer)	**27**	**30**	**28**	**45**	**24**	**46**	**200**	
	Omission error	0.074	0.166	0.179	0.088	0.166	0.108		

Table 16.12 Comparison of the different accuracy parameter, overall accuracy and kappa coefficient (2000)

Land use categories	User accuracy calculation	Producer accuracy calculation	Overall accuracy	Kappa coefficient (T)
River and canal	80.65	92.59	**87.50%**	**84.80%**
Water bodies	83.33	83.33		
Forest area	82.14	82.14		
Agricultural area	91.11	91.11		
Bare/Exposed soil	90.91	83.33		
Built-up area	93.18	89.13		

Table 16.13 Computation of confusion matrix SVM algorithm for accuracy assessment of LULC map of 1990, Bolpur town

Classified data (image to be evaluated)	Reference data (ground truth data)								
	Land use categories	River and canal	Water bodies	Forest area	Agricultural area	Bare/Exposed soil	Built-up area	Total (user)	Commission error
	River and canal	**22**	3	0	0	2	2	**29**	0.241
	Water bodies	2	**27**	1	0	0	2	**32**	0.156
	Forest area	1	2	**23**	2	1	0	**29**	0.206
	Agricultural area	0	0	2	**37**	0	2	**41**	0.097
	Bare/Exposed soil	0	0	0	2	**26**	0	**28**	0.071
	Built-up area	0	0	2	0	1	**38**	**41**	0.073
	Total (producer)	**25**	**32**	**28**	**41**	**30**	**44**	**200**	
	Omission error	0.120	0.156	0.178	0.097	0.133	0.136		

Table 16.14 Comparison of the different accuracy parameter, overall accuracy and kappa coefficient (1990)

Land use categories	User accuracy calculation	Producer accuracy calculation	Overall accuracy	Kappa coefficient (T)
River and canal	84.62	88.00	90.50%	88.52%
Water bodies	87.88	90.63		
Forest area	80.65	89.29		
Agricultural area	94.87	90.24		
Bare/Exposed soil	92.86	86.67		
Built-up area	97.67	95.45		

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