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Remote Sensing Assessment of the Impact of Land Use and Land Cover Change on the Environment of Barddhaman District, West Bengal, India

Saidur Rahaman[1†], Pankaj Kumar[2*], Ruishan Chen[1], Michael E. Meadows[1,3,4] and R. B. Singh[2]

[1] Key Laboratory of Geographic Information Science, Ministry of Education, School of Geographical Science, East China Normal University, Shanghai, China, [2] Department of Geography, Delhi School of Economics, University of Delhi, New Delhi, India, [3] Department of Environmental and Geographical Science, University of Cape Town, Cape Town, South Africa, [4] College of Geography and Environmental Sciences, Zhejiang Normal University, Jinhua, China

Land transformation is caused by natural as well as anthropogenic driving forces and its impact on the regional environment is a key issue in understanding the relationship between society and the environment. Here, we investigate Land Use Land Cover (LULC) change over four decades, based on Landsat satellite imagery for 1987, 1997, 2007, and 2017, for the Barddhaman district of West Bengal, India. In total, six land use and land cover types have been identified. Over the period in question, there are notable increases in the area under built-up land, plantations and water bodies, whereas there has been a marked decrease in forest cover, agricultural land, and in bare land. The diverse effects of land transformation on the natural environment have been assessed using Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Leaf Area Index (LAI), Effective Roughness Length (ERL), and Surface Albedo (SA). Overall, mean annual LST increased by 2.91°C during the study period, while there were reduced values for vegetation indices and an increase in the water index over the period 1987–2017. LAI and ERL both exhibit notable decreases, although the pattern was not uniform across the study area. For example, LAI values increased over time in the Kalna, Memari, Jamalpur, Ausgram, and Kanksa regions. In Faridpur-Durgapur, Raniganj, Asansol, and Raina, increases in surface albedo and ERL were more marked than in other regions. Negative correlations are found between LST-NDVI and NDVI-NDWI, while there is no correlation between LST and NDWI. During the period 1987–2017, NDVI values have declined, although the NDWI shows no clear trend. LULC change is shown to have had a series of negative impacts on the environment of the Barddhaman district. In response, technological, economic, policy, or legislation measures are needed to restore degraded ecosystem services in the district as well as other areas where similar impacts are experienced.

Keywords: environmental change, surface albedo, LULC, LST, LAI, NDVI, NDWI

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***Correspondence:**
Pankaj Kumar
pankajdsedu@gmail.com

†ORCID:
Saidur Rahaman
orcid.org/0000-0002-1593-272X

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INTRODUCTION

Land use change, land cover conversion and land use management interventions have greatly altered a large proportion of the earth's surface to meet increasing demands for natural resources (Vitousek, 1997; Foley et al., 2005; Rahman et al., 2012; Song et al., 2018). Rising human population is the main driving force directly responsible for land use and land cover (LULC) change in any region (Briassoulis, 2009). Land use change is often associated with ecosystem degradation although, if judiciously managed, it may improve ecosystem quality (Koellner and Scholz, 2008). Urbanization, unplanned industrialization and associated rapid population growth have obvious negative effects on the regional environment (Kurucu and Chiristina, 2008) and inappropriate land use practices also have deleterious effects on natural systems (Gupta and Roy, 2012). On the other hand, increases in vegetation, particularly in forest cover and in water bodies, may have more positive effects on the natural environment (Trombulak and Frissell, 2000; Myhre et al., 2013; Sahim, 2018).

Several previous studies have described air quality and its impact on the surrounding environment of Barddhaman (Reddy and Ruj, 2003; Gupta et al., 2009; Chatterjee, 2011; Banerjee, 2013; Palit et al., 2013; Roy et al., 2015; Chattopadhyay et al., 2017; Dey et al., 2017). Others have used remote sensing or census data to describe land use and land cover change arising from urban and industrial expansion (Sikdar et al., 2004; Chatterjee et al., 2012; Gupta and Roy, 2012; Banerjee, 2013). However, none of these studies has thus far considered the impact of land use and land cover change on the range of environmental indicators that are the focus of this study.

The process of land use land cover (LULC) change can take place naturally or anthropogenically at scales ranging from local to regional. One of the most widely reported drivers is population increase and urbanization associated with related demands on land. Typically, as is shown in this study, a rapid increase in built up area results in widespread land use and land cover change with intendent negative impacts on a wide range of environmental indicators, including LST, NDVI, NDWI, and LAI. Ultimately, such processes are unsustainable and eventuate a decrease in overall environmental health in a region.

The diverse environmental impacts of LULC have been investigated by various means, including remote sensing assessment of surface changes using, for example, LAI, LST, NDVI, and NDWI (Gao, 1996; Fu, 2003; Feddema et al., 2005; Bonan, 2008; Oliver and Moorcroft, 2014; Laxmi, 2015; Baeza and Paruelo, 2020). LST is often utilized in studies of global temperature change, as well as in hydrological, geo-biophysical and LULC investigations (Cihlar, 2000; Mehdi et al., 2016; Zhang et al., 2016a; Alexander, 2020). In this study, LST, NDVI and NDWI have been utilized, as well as the relationships between them, as these indices integrate a range of environmental variables. For example, LST is influenced by vegetation cover, the albedo effect, soil moisture content (Charney et al., 1977; Arbia et al., 1998) and soil temperature (NASA, 2017).

The Barddhaman district is one of the most important industrial regions of India (Higher Education Department, 1997). There were just 18 industrial units in the district before the 1990s, but this had increased to 38 by 2015, accompanied by an increase in the size of the industrial area from 2133 acres to 4581 acres, including an industrial park (Higher Education Department, 1997; Economic Review of 2011-12, 2013; Msme-Development Institute, 2016). A substantial proportion of this new industrial land was converted from agriculture (Bureau of Applied Economics and Statistics, 1995/2006/2015). As such, there have been substantial land use changes arising from industrial expansion in the district which are representative of rapidly industrialized regions in India and in the developing world in general. Much of the rest of the district is still occupied by agricultural land, followed by plantation and built-up land, while only a relatively small proportion is occupied by forest cover, which has been subject to significant clearance between 1987 and 2017.

Recent changes in land use are known to have been both substantial and rapid but there has to date been no assessment of their nature, rate and scale, or indeed of their possible broader environmental impacts. The main aim of this research, therefore, is to describe and account for the changing spatial and temporal patterns of LULC in the Barddhaman district between 1987 and 2017and to assess the impact of LULC change on key environmental parameters, including LST, NDVI and NDWI.

STUDY AREA

The Barddhaman district of West Bengal is located between 22°56′ and 23°53′N and 86°48′ and 88°25′E. The district is bounded to the north by Birbhum, Murshidabad and a part of Bihar, to the east by Nadia, to the west by Dhanbad; to the south the district is bounded by Hooghly, Bankura, and Purulia districts of West Bengal (Higher Education Department, 1997; Annual Administrative Report of Barddhaman Collectorate (Office of the District Magistrate and Collector, 2014; **Figure 1**).

The climate is broadly speaking of the warm savanna type, with mean daily temperatures of the district in summer of around 30, and 20°C in winter, while mean annual rainfall approximates 1500 mm with much of this falling in the monsoon season from June to mid-September (Higher Education Department, 1997). Topography is varied, as the area is transitional between the undulating Jharkhand plateau in the west and the alluvial plain of the Ganga-Brahmaputra to the north and east. Overall, soils are typically rich in clay, although sandier soils are associated with the alluvial plains (Annual Administrative Report of Barddhaman (Office of the District Magistrate and Collector, 2014). According to the most recent (2011) census of India, the total population of Barddhaman district was 7,723,663 with a population density of 1,099 per km^2. Barddhaman is the third and seventh most populous district of West Bengal and India respectively, and the proportion of its population living in urban areas increased from 36.9 to 39.9% between 2001 and 2011 (Census of India, 2011). Conditions in Barddhaman are suited to both agriculture and industrial development. Some 58% of the

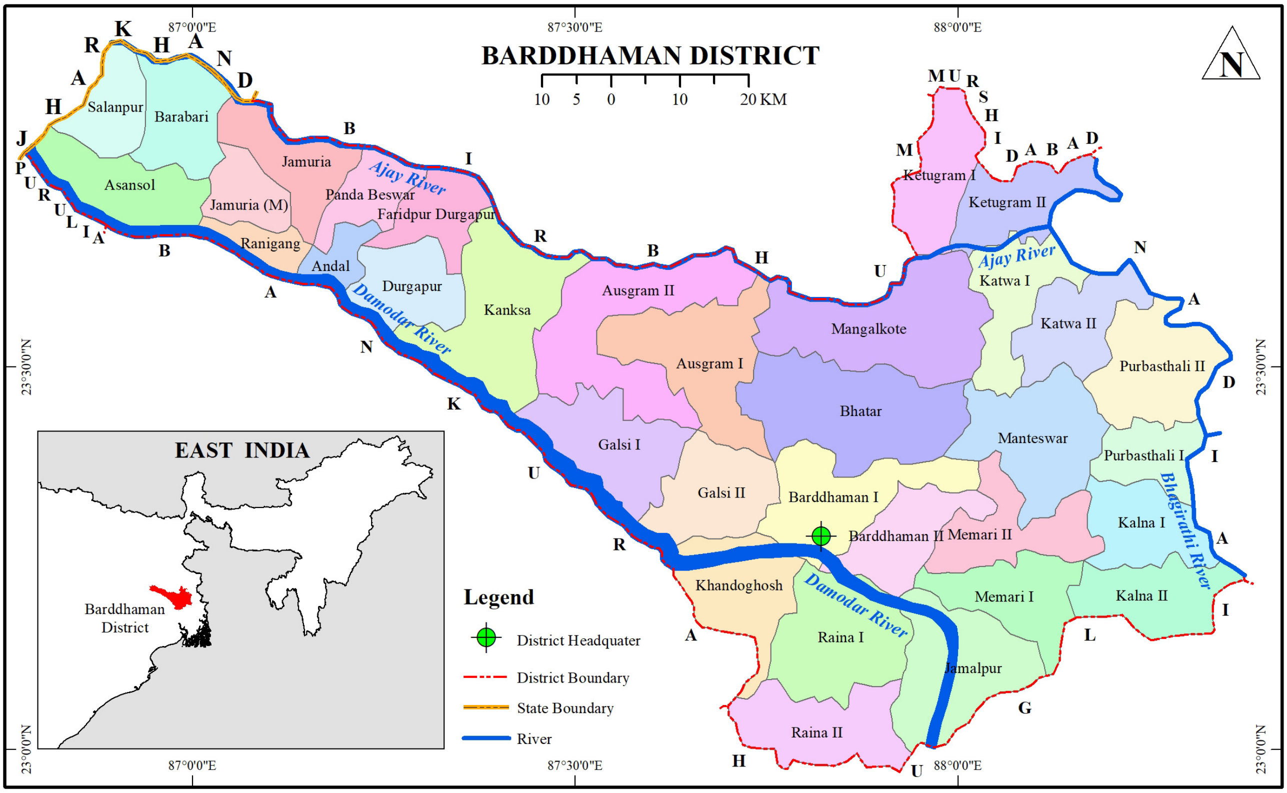

FIGURE 1 | Locational and administrative map of Bardhhaman district. Source: Survey of India and the National Informatics Centre (NIC), 2017.

total population is dependent on primary economic activities, especially agriculture and, in terms of mineral resources, Barddhaman is regarded as one of the premier districts in India (Economic Review of 2011-12, 2013).

MATERIALS AND METHODS

The purpose of the study is to evaluate the impact of LULC change, using several indicators, on a number of environmental variables. The LULC study was based on supervised classification of satellite imagery from Landsat 5 Thematic mapper (TM) Landsat 8 OLI/TIRS (Li et al., 2013) for the years 1987, 1997, 2007, and 2017. The data products for surface albedo, LAI, ERL, including LULC were calculated for the month of May. Surface albedo and ERL were calculated with time averaged 0.25° data sets taken from the OMI model, Global Modeling and Assimilation Office, NASA, whereas MODIS 8 day time-averaged data at 250 m resolution were obtained for LAI.

In this study, six major LULC classification types were identified based on the USGS-LULC classification system. Remote sensing, when incorporated with GIS, enables accurate land use classification and change over time (Richards, 1993). LAI, surface albedo, and the effective roughness length were also measured to account for the spatio- temporal variation of vegetation cover and temperature effect on the surrounding environment.

Data Analysis

In addition, radiometric correction including Haze reduction, Noise reduction and several other atmospheric corrections have been processed in ERDAS and ArcMap for better estimation of land use and land cover. Maximum Livelihood techniques were used for Supervised Classification. In all, 300 random samples were used for Kappa Accuracy Assessment, whereby more than 80% Kappa values were obtained. Six categories of land use and land cover were identified from the Landsat datasets. For the purpose of this study, a total of 30 LST random samples were taken to measure the trend in LST under different land uses and land covers for different years. The calculation of LST is presented in section "Calculation of LST" in detail. NDVI values were divided into the three categories *viz.* < 0, 0–0.255, and > 0.255; NDWI values were categorized into < 0, 0–0.1, and > 0.1. MODIS data products with 8 days time-averaged with 250 m spatial resolution has been processed for this study for LAI. On the other hand, surface albedo and effective roughness length with 0.25° time-averaged data sets were directly processed by the spatial analysis tool in ArcMap. Finally, a correlation matrix analysis, indicating correlation coefficients and level of statistical significance was constructed to investigate the nature of relationships between the multiple variables.

A total of 100 random points ($N = 100$) was sampled for each of the indicators in order to achieve this (**Figure 8**). The

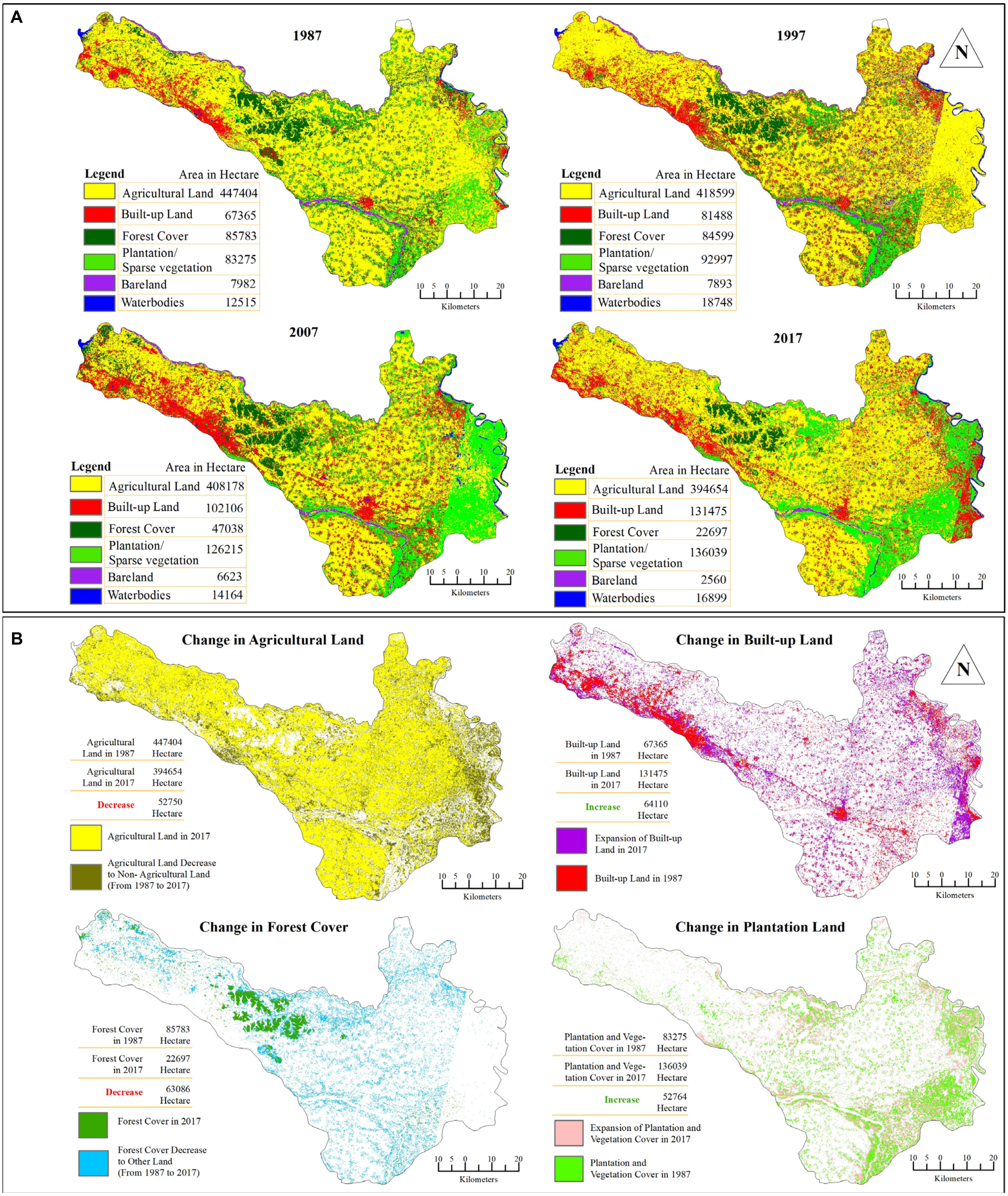

FIGURE 2 | (A) LULC (1987, 1997, 2007, and 2017). **(B)** LULC change (1987–2017). Author, 2019. (Landsat 5 and 8 satellite imagery, USGS). Author, 2019. (Area calculated from satellite Landsat imagery by supervised classification method in Erdas Imagine 14 and ArcGIS).

correlation matrix shows that LST and NDVI are negatively correlated, that there is a strong negative correlation between NDVI and NDWI, and that there is no correlation between LST and NDWI. A strong negative correlation is evident between NDVI and NDWI. The relationship between LST and NDVI is negative (degree of correlation or R^2 = 0.054 and regression

TABLE 1 | LULC change in Barddhaman district (1987–2017).

Period	1987–1997		1997–2007		2007–2017		1987–2017	
LULC	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**
Agricultural land	−28805	−6.43	−10421	−2.48	−13524	−3.31	−52750	−11.79
Built-up land	14123	20.96	20618	25.31	29369	28.76	64110	95.16
Forest cover	−1184	−1.38	−37561	−44.39	−24341	−51.74	−63086	−73.54
Plantation land	9722	11.6	33218	35.71	9824	7.78	52764	63.36
Bare land	−89	−1.12	−1270	−16.09	−4063	−61.34	−5422	−67.92
Water bodies	6233	49.84	-4584	−24.45	2735	19.31	4384	35.03

Calculated by Author, 2017. A. Area change in hectare, B. Area change in percentage.

TABLE 2 | Change detection matrix of land use and cover, 1987–2017.

		2017						
1987	**LULC (in Hectare)**	**Bare land**	**Built-up land**	**Agricultural land**	**Plantation land**	**Forest cover**	**Water-bodies**	**Total**
	Bare land	1692	296	4540	609	1	845	7982
	Built-up land	16	36,020	16,862	10,934	1720	1814	67,366
	Agricultural land	470	68,582	317,412	51,772	3011	6158	447,404
	Plantation land	51	10,763	20,767	49,989	782	924	83,276
	Forest cover	32	13,994	31,399	22,679	17,159	520	85,783
	Water bodies	300	1436	2733	1417	25	6605	12,515
	Total	2561	131,091	393,713	137,399	22,697	16,866	704,326
	LULC (in%)	**Bare land**	**Built-up land**	**Agricultural land**	**Plantation land**	**Forest cover**	**Water-bodies**	**Total**
	Bare land	0.2402	0.0420	0.6446	0.0863	0.0001	0.1201	1.1333
	Built-up land	0.0023	5.1141	2.3941	1.5524	0.2442	0.2575	9.5646
	Agricultural land	0.0668	9.7372	45.0659	7.3506	0.4274	0.8743	63.5222
	Plantation land	0.0072	1.5281	2.9485	7.0974	0.1111	0.1312	11.8235
	Forest cover	0.0045	1.9869	4.4580	3.2201	2.4362	0.0738	12.1794
	Water bodies	0.0426	0.2038	0.3880	0.2012	0.0036	0.9378	1.7770
	Total	0.3636	18.6121	55.8991	19.508	3.2226	2.3946	100

Calculated by Author, 2017.

function: $y = 20.5 + [-]3.31 \times x$), no correlation is observed between LST and NDWI (degree of correlation or $R^2 = 0.024$ and regression function: $y = 20.34 + 2.38 \times x$), NDVI and NDWI are very markedly negatively correlated (degree of correlation or $R^2 = 0.734$ and regression function: $y = 0.02 + [-]0.93 \times x$) (**Figure 8** and **Table 4**). Only NDWI and NDVI are positively correlated (degree of correlation or $R^2 = 0.234$ and regression function: $y = 0.08 + 0.51 \times x$) (**Figure 8** and **Table 4**).

Calculation of LST

Land surface temperature was calculated for the month of May, a largely cloud-free month in the Bardhhaman district. In total, 30 random pixel samples were taken to measure the trend in LST for years 1987, 1997, 2007, and 2017. Five different LST categories were identified in this study, *viz.* < 25.50 Celsius (c), 25.51–27.15 c, 27.16–28.85 c, 28.86–30.50 c, and > 30.50 c.

Calculation of Radiance

Thermal infrared for Landsat 8 and Thermal band for Landsat 5 were used in this study and radiance calculated using the raster calculator tool in Arc GIS. Following this step, Landsat 8 OLI and TIRS band (Barsi et al., 2014) data were converted to TOA spectral radiance using the radiance rescaling factors provided in the metadata file (USGS, 2017).

$$L\lambda \ = \ M_L^* Q_{cal} \ + \ AL \tag{1}$$

Where:

$L\lambda$ = TOI spectral radiance [watts/(m2 * srad* µm)]

M_L = band specific multiplicative rescaling factor (actually thermal infrared band)

Q_{cal} = quantized and calibrated standard product pixel values (DN)

A_L = the band specific additive rescaling factor.

Conversion to at- Satellite Brightness Temperature

The following equation was used to calculate the satellite brightness temperature.

$$BT = \frac{K_2}{ln[\left(\frac{K_1}{L\lambda}\right) + 1} - 273.15.$$

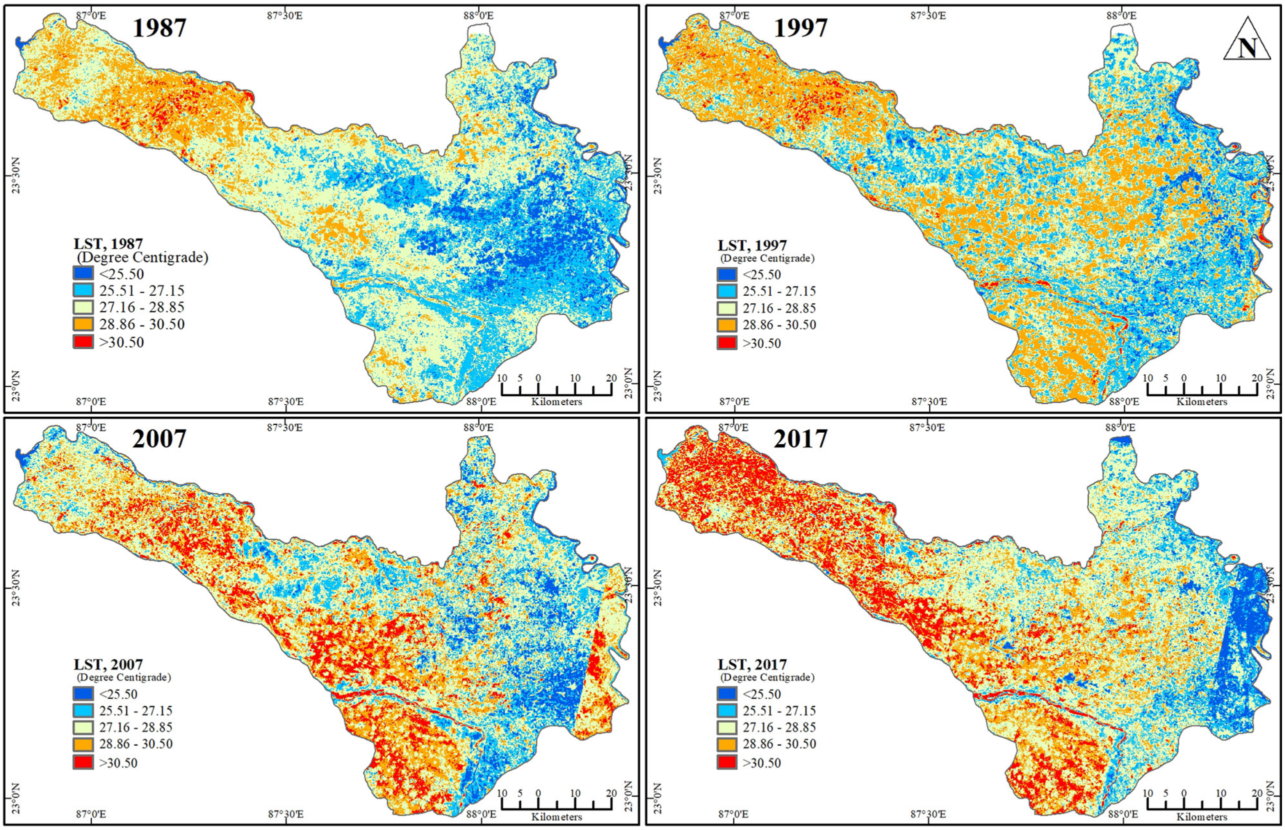

FIGURE 3 | LST of Barddhaman district (1987, 1997, 2007, and 2017). Source: Author, 2019. (Landsat 5 and 8 satellite imagery, USGS).

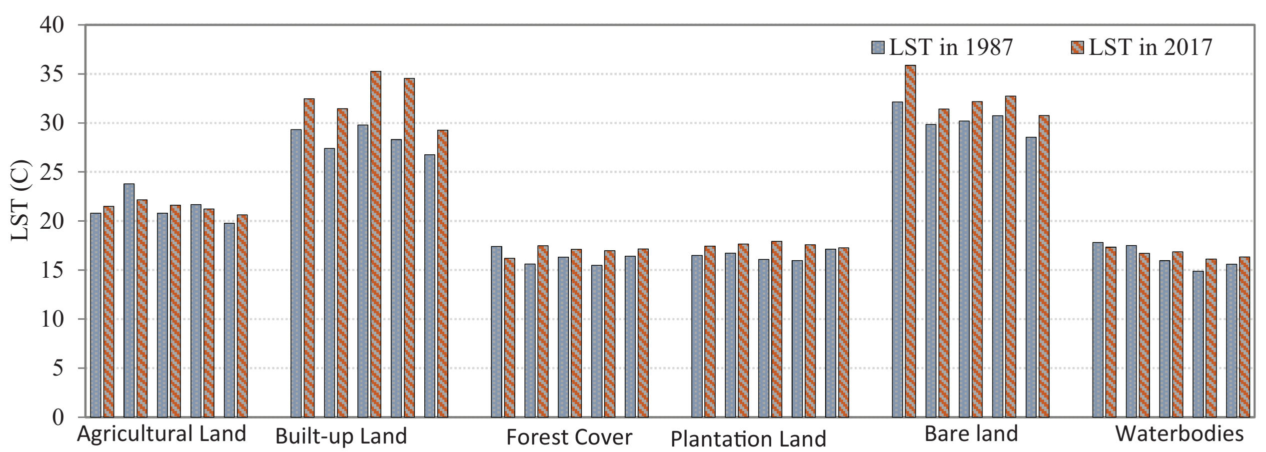

FIGURE 4 | LST in different LULC categories (1987–2017).

Where:

BT = satellite brightness temperature

K_1 and K_2 = stand for the band specific thermal conversion constants

ln = log number (formula tools in raster calculator, ArcGIS)

$L\lambda$ = radiance

273.15 = conversion factor Kelvin to Celsius.

The NDVI Method for Emissivity Correction

The emissivity correction was obtained via NDVI. The proportion of the vegetation (P_V) and its emissivity (ε) were calculated from the following formulae.

$$\text{NDVI} = (\text{NIR}-\text{VIS})/(\text{NIR} + \text{VIS})$$

TABLE 3 | LST (°C) of Barddhaman district, 1987 and 2017.

Study sites	Coordinates	LULC	LST in 1987	Avg. temp.	LST in 2017	Avg. temp.
1	87.685010 23.378190	Agricultural land	20.82	21.376	21.51	21.436
2	87.678654 23.379652		23.79		22.18	
3	87.868083 23.070173		20.81		21.63	
4	88.142581 23.738722		21.69		21.24	
5	87.076540 23.771435		19.77		20.62	
6	87.871598 23.241786	Built-up land	29.33	28.328	32.49	32.614
7	87.837863 23.233141		27.41		31.47	
8	87.463643 23.444283		29.81		35.27	
9	87.375222 23.494988		28.32		34.56	
10	87.304945 23.538337		26.77		29.28	
11	87.394087 23.593214	Forest cover	17.42	16.252	16.21	16.991
12	87.392721 23.519424		15.62		17.49	
13	87.631855 23.504393		16.32		17.11	
14	87.547589 23.557230		15.49		16.98	
15	87.438270 23.593214		16.41		17.16	
16	87.737984 23.512136	Plantation land	16.49	16.486	17.45	17.578
17	87.937946 23.571806		16.73		17.66	
18	87.640054 23.265715		16.09		17.93	
19	87.967097 23.048445		15.98		17.58	
20	88.013284 23.849171		17.14		17.27	
21	87.653352 23.604628	Bare land	32.15	30.305	35.89	32.604
22	87.620357 23.238806		29.86		31.43	
23	87.987704 23.121038		30.19		32.18	
24	87.788674 23.238917		30.74		32.75	
25	87.098630 23.796663		28.56		30.77	
26	86.828323 23.817602	Water bodies	17.82	16.358	17.34	16.682
27	87.130991 23.761447		17.51		16.72	
28	88.134172 23.661510		15.96		16.88	
29	88.357841 23.370264		14.89		16.13	
30	87.979983 23.040946		15.61		16.34	

Calculated by Author, 2017. Date and time of data accusation: 6th May, 1987 at 13.04.33 and 18th May, 2017 at 11.27.54 from USGS.

Calculating the Proportion of Vegetation

The proportion of vegetation (P_V)was calculated using the following formula using computed values forradiance, satellite temperature and the vegetation index.

Pv = [(NDVI–NDVI$_{min}$)/(NDVI$_{max}$–NDVI$_{min}$)]^2 Where:

Pv = proportion of vegetation
NDVI$_{min}$ = minimum value of NDVI
NDVI$_{max}$ = maximum value of NDVI.

Calculating Land Surface Emissivity (LSE)

Land Surface Emissivity [LSE (ε)] calculation is required in order to estimate LST, since the LSE is a proportional factor that scales radiance to predict emitted radiance, and LSE is the efficiency of transmitting thermal energy across the surface into the atmosphere (Jiménez-Munoz et al., 2006). LSE was calculated as follows:

$$\varepsilon_\lambda = \varepsilon_{v\lambda} P_v + \varepsilon_{s\lambda}(1 - -P_v) + C_\lambda \quad (2)$$

Where:

ε_v and ε_s = emissivity of the vegetation and soil, respectively

C = represents the surface roughness (C = 0for homogenous and flat surfaces) taken as a constant value of 0.005

P_v = proportion of vegetation
0.004 and 0.986 = constant value.

Land Surface Temperature (LST)

Finally, land surface temperature was calculated from the following formula:

LSTs = BT/1 + w * (BT/p) * ln (e)

Where:
LSTc = land surface temperature in degrees centigrade
BT = satellite brightness temperature
1 = constant factor
w = wavelength of emitted radiance (11.5μm)
p = h * c/s (1.438 * 10^{-2} m K) or constant value of p = 14380
ln = log number
(e) = emissivity.

Normalized Difference Water Index (NDWI)

NDWI measures changes related to water bodies, using green and near infra-red (NIR) wavelengths (McFeeters, 1996) as follows:

NDWI = (Green–NIR)/(Green + NIR).

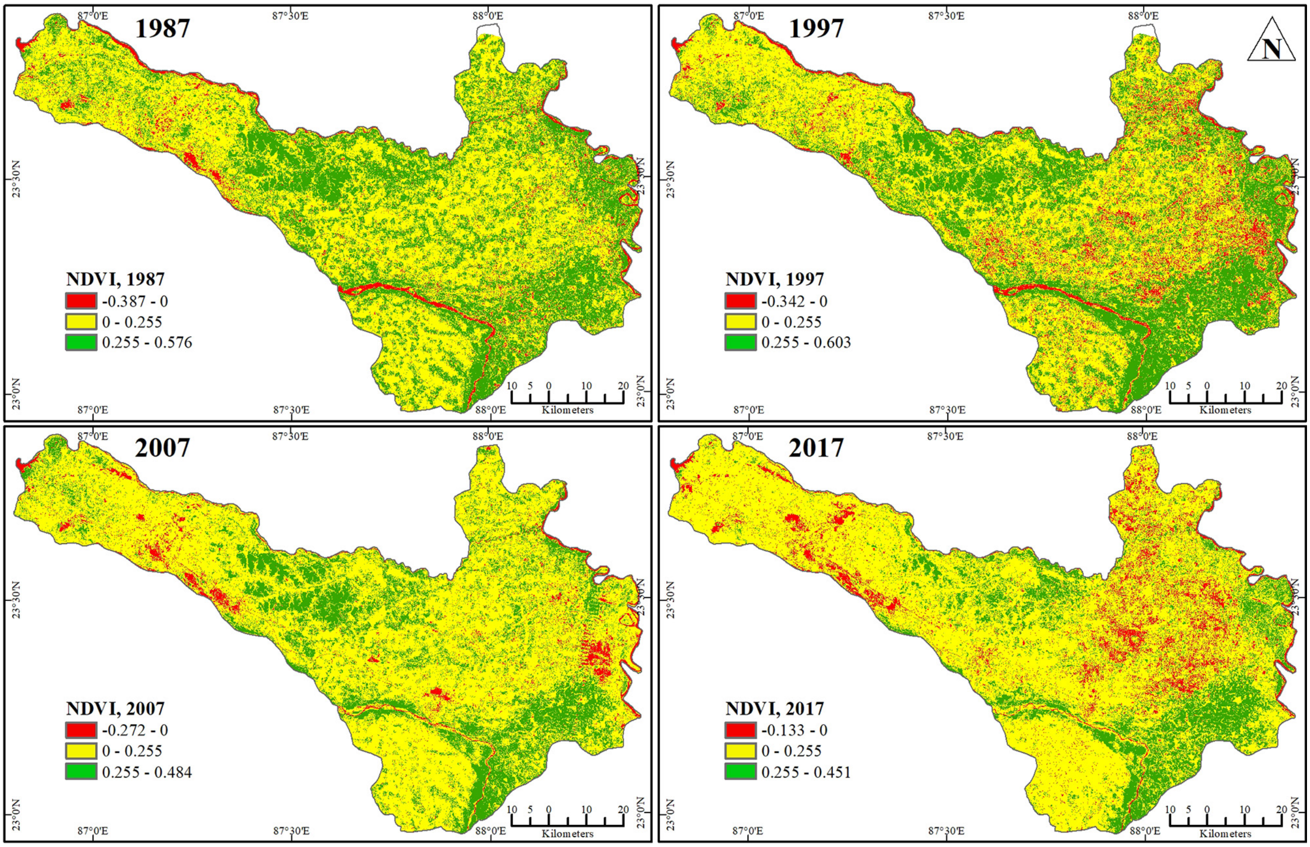

FIGURE 5 | Normalized Difference Vegetation Index (NDVI). Author, 2019. (Landsat 5 and 8 satellite imagery, USGS).

Leaf Area Index (LAI)

LAI is calculated as per Maynard and Royer (2004).

$$1/[\ln\left(\frac{Z_b}{Z_0^e}\right)]^2 = \sum_i fi * 1/[\ln\left(\frac{Z_b}{Z_0^i}\right)]^2 \quad (3)$$

Where:

fi = the fractional area of each LULC category i,

= the roughness length,

Z_b = the height of the first atmospheric model level above the ground (i.e., 65 m).

RESULTS

LULC Change

Figure 2 and **Table 1** reveal that agricultural land has declined between 1987 and 2017by 28,805 hectares, representing almost 12% of the original total. The rate of conversion of agricultural land appears to have increased, with 10,421 hectares lost between 1997 and 2007, and a further 13,524 hectares between 2007 and 2017. By contrast, built–up land almost doubled in area between 1987 and 2017, increasing from 14,123 hectares (20.96%), 20,618 hectares (25.31%) and 29,369 hectares (28.76%) for the periods 1987–1997, 1997–2007 and 2007–2017 respectively. The increase has been continuous, but most pronounced within the last ten years (**Table 1** and **Figure 2**).

Forest cover decreased by 73.54% from 1987 to 2017, recording especially high losses in the last decade. The most significant reductions in forest cover of the Barddhaman district were especially prominent in northern Durgapur, but also marked in Ausgram and Kanksa. Plantations increased between 1987 and 2017 by 52,764 hectares (63.36%), with higher expansion rates between 1997 and 2007 than in other periods (**Table 1** and **Figure 2**).

Accuracy Assessment

The overriding assumption in any image accuracy assessment procedure is that the area for which it is conducted is representative of the entire area mapped from remotely sensed data (Congalton, 1991; Jensen, 2015). Kappa accuracy assessment is carried out to reflect the difference between actual agreement and the agreement expected by chance, and is an important statistical method in the process of analyzing remote sensing quantitative data (Congalton, 2004). A Kappa value of 0.85 means that there is 85% better agreement than by chance alone (Congalton and Mead, 1986). The LULC classified images used in this study result in Kappa

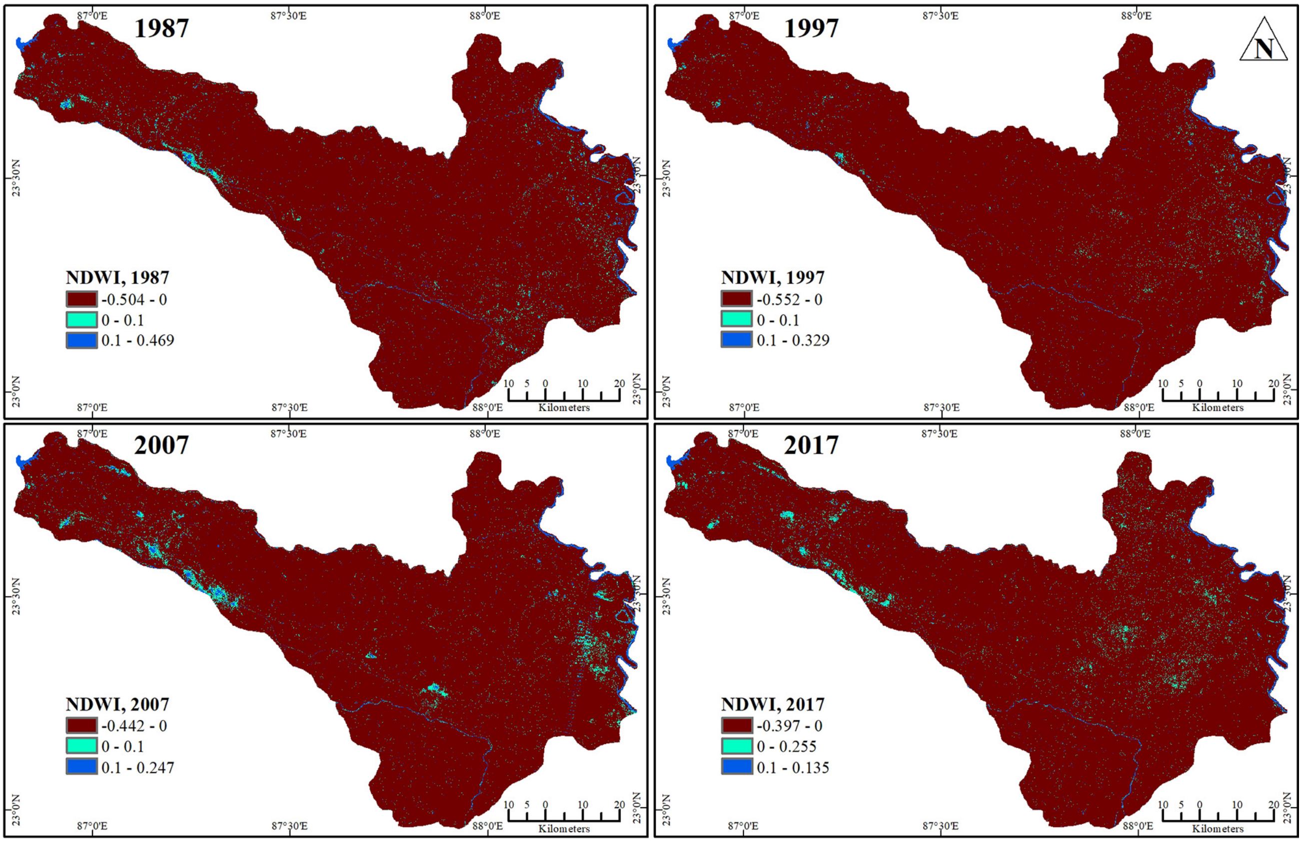

FIGURE 6 | Normalized Difference Water Index (NDWI). Author, 2019. (Landsat 5 and 8 satellite imagery, USGS).

values of 0.8209, 0.8012, 0.8437, and 0.8485 in 1987, 1997, 2007, and 2017, respectively, whereas the overall accuracy exceeds 80% throughout and may be regarded as acceptable (Bharatkar and Patel, 2013).

Land Use Land Cover Change Detection Matrix (1987–2017)

The LULC change detection matrix (**Table 2**) presents data revealing changes that occurred in each category over the 30 years period under consideration. The matrix indicates considerable change in agricultural land followed by plantation and built-up land. A substantial proportion of agricultural land has been converted into built-up land and plantations. **Table 2** also indicates major changes in dense forest cover.

Spatial and Temporal Change of LST, NDVI, NDWI, and LAI

In 1987, the highest and lowest LSTs recorded for May were 36.24 and 15.27°C, respectively. **Figure 3** shows that, by 2017, the maximum LST was almost 3.0°C higher than 30 years earlier during the same month. Minimum temperatures also increased, from 15.27°C in 1987 to 16.66°C in 2017.

Notably, LST values were higher on built-upland than on any other LULC type (**Figure 4** and **Table 3**). The mean monthly LST of agricultural land was 21.37°C in 1987 and 21.43°C in 2017, while the mean temperature of built-up land increased by about 4.29°C. The mean monthly temperature of plantation land was 16.48°C in 1987 and 17.57°C in 2017, an increase of 1.09°C, while there was an increase of around 0.75°C on land occupied by forest. The mean LST of water bodies was 16.35°C in 1987 and 16.68°C in 2017. The lowest rate of increase in LST is found in water bodies and under forest cover.

Pixel values of NDVI for three different categories (below 0, 0–0.255 and above 0.255) show spatial and temporal variation across the region. In general, NDVI exhibits a negative trend during the period 1987–2017 (**Figures 5**, **10A**). The most notable change occurred in the Kanska, Faridpur Durgapur and Ausgram regions, where vegetation cover is highest. The south-eastern part of the district especially was subject to substantial increases in the areas of plantation land between 1987 and 1997, although after this date 1997, NDVI values decreased (**Figure 5**).

NDWI values from 1989 to 2017 indicate that the total area and depth of water bodies, including rivers, lakes, ponds and wetlands, increased between 1987 and 2017 (**Figure 6**).

Leaf Area Index (LAI) is the total one-sided (or one half of the total all-sided) green leaf area per unit ground surface area (Chen and Black, 1992) and is a measure of biological productivity.

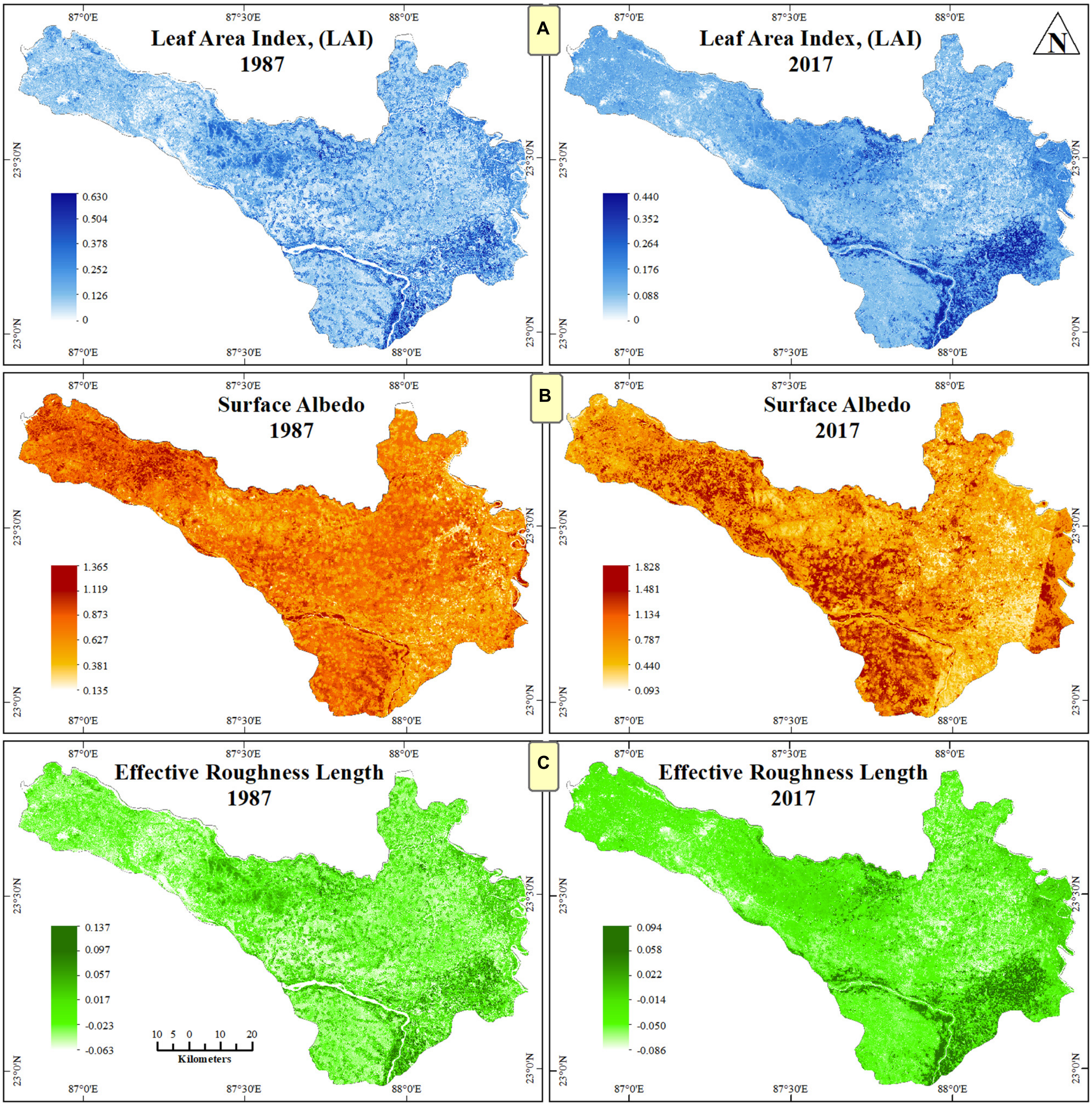

FIGURE 7 | Differences in **(A)** Annual mean LAI, **(B)** Land surface albedo (×), and **(C)** Effective roughness length (unit: m) in two difference year (1987 and 2017) using 8 days time average with 250 m spatial resolution taken from MODIS product for LAI; time average with 0.25° data sets taken from the OMI model, AVHRR data for SA and ERL (Loveland et al., 2000).

Figure 7 illustrates that LAI and effective roughness length show a decreasing trend between 1987 and 2017 in the Barddhaman district. Higher LAI values are found in the south-eastern parts (Kalna-Memari-Jamalpur) as well as in the Ausgram- Kanksa region (**Figure 7A**). Conversely, surface albedo shows a notable increase in these same regions (**Figure 7B**). Change in surface albedo and effective roughness length values in Faridpur Durgapur, Raniganj, Asansol, and Raina was greater than in other regions of the district over the period (**Figure 7C**).

Multiple Correlation Matrix Analysis of LST, NDVI, and NDWI

With the help of correlation matrix analysis (**Figure 8** and **Table 4**), the relationships between LST with NDVI, LST with

TABLE 4 | Pearson's correlation and descriptive statistics.

Variable	LST	NDVI	NDWI	Variable	Mean	*SD*
LST	1	-0.233	0.154	LST	20.05	2.13
NDVI	-0.233	1	-0.857	NDVI	0.14	0.15
NDWI	0.154	-0.857	1	NDWI	-0.12	0.14

N = *100.*

NDWI and NDVI with NDWI have been established to further analyses the characteristics of change over time (Cohen, 1960).

DISCUSSION

The study reveals conspicuous decreasing trends in agricultural land, forest cover and bare land in the Barddhaman district over the period 1987–2017, in particular due to the expansion of built-up land, whereas there is a less consistent increasing trend recorded in areas occupied by plantations and water bodies (**Figure 2**). Numerous previous studies have also noted marked losses of agricultural land and forest cover due to urban expansion in South Asia (e.g., Nor et al., 2017; Aoshima et al., 2018) most notably in urban regions of India (Moghadam and Helbich, 2013). Published statistics are compatible with the observed changes; the Barddhaman (Bureau of Applied Economics and Statistics, 1995/2006/2015) and Higher Education Department (1997) report that more than 25% of the land was developed and that forest cover declined more than 65% within the last three decades. LULC change has been accompanied by an overall increase in LST of 2.91°C. The analysis reveals that, over the period under consideration, there are consistently increased temperatures across the district. Of the five LST categories, the areas with values < 25.50

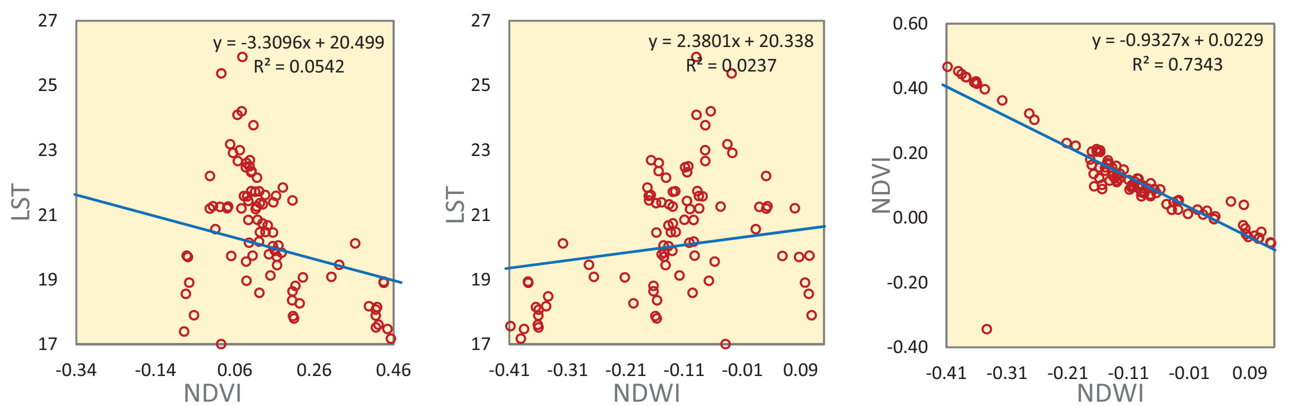

FIGURE 8 | Multiple correlation analysis of LST, NDVI, NDWI, (*N* = 100, Significant Correlation at the 0.01 level), of Barddhaman district, 2017. Method Testified in ArcGIS, Erdas Imagine Software, Microsoft Excel and SPSS.

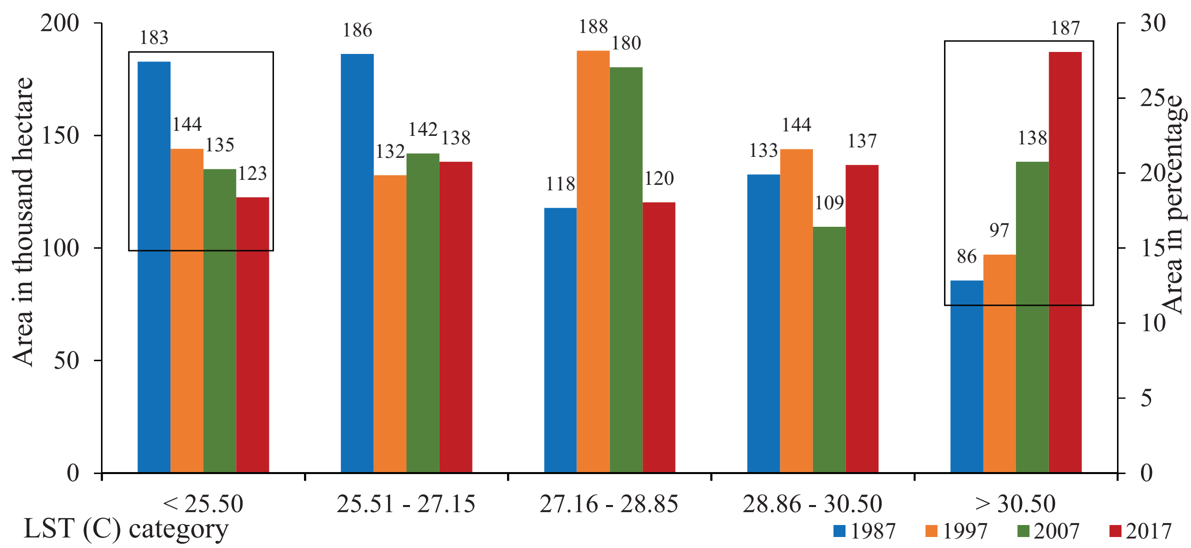

FIGURE 9 | Total area converted in different LST category (1987, 1997, 2007, and 2017).

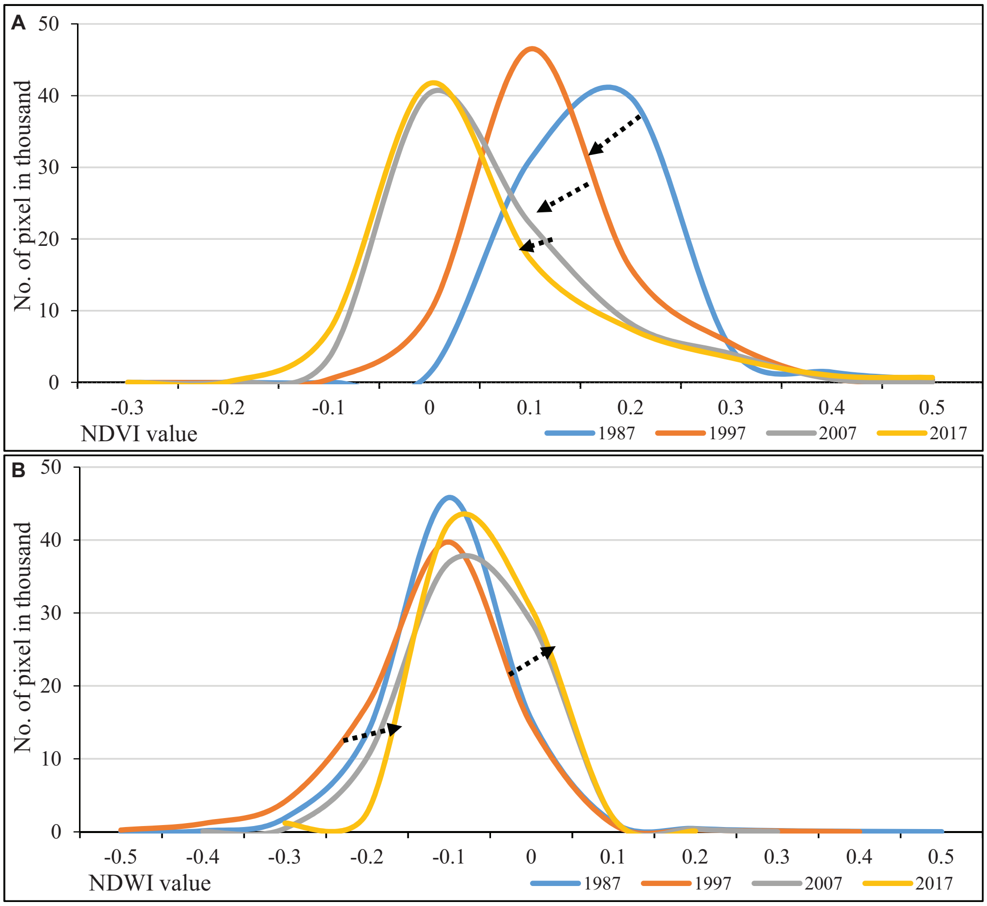

FIGURE 10 | Pixel identification of **(A)** NDVI and **(B)** NDWI, (1987, 1997, 2007, and 2017).

decreased most markedly. The second (25.51–27.15), third (27.16–28.85) and fourth (28.86–30.50) LST categories were more variable, but a marked increasing trend was found in the > 30.50 category. The analysis clearly depicts that, between 1987 and 2017, temperatures increased across the district overall (**Figure 9**).

NDVI, LAI and effective roughness length all show a decreasing trend over the period in question. These observations are consistent with the findings of Cao et al. (2015) and Mahmood et al. (2010) among others, who also note adverse environmental effects of land conversation, including on LST. Indeed, many studies have concluded that LST is negatively correlated with forest cover (or any other green space in general), while built-up land is positive correlated with temperature (Mallick and Rahman, 2012). The findings of this study confirm that LSTs are higher, and increase more markedly, in areas of lower vegetation cover (**Figures 3**, **5**). The cooling effects of vegetation are well known and the authorities need to take this into account in urban planning and design (Hang and Rahman, 2018). The diverse negative effects of land transformation on the natural environment are revealed in this study which records increased LST mainly as a consequence of the loss of forest cover and the increase in built-up land (**Figures 2**, **10A**). This is also evident in changes in various biophysical parameters, including LAI (**Figure 7A**) and NDVI which has decreased in recent decades (**Figure 10A**).

Forest cover decline has been most prominent in Panda Beswar, Faridpur, Kanksa, and Ausgram regions (**Figure 2**), mainly due to the expansion of agricultural land (**Figure 2A**), an observation also recorded in the Bureau of Applied Economics and Statistics (1995/2006/2015). The maximum expansion of built-up land was found in Durgapur, Raniganj and Asansol urban regions, associated with loss of agricultural and bare land which may have accentuated the observed increases in LST in this region (**Figures 2**, **3**). This is consistent with many other studies (for example Kurucu and Chiristina, 2008; Fang et al., 2016; Zhang et al., 2016b) that demonstrate the expansion of built-up land negatively impacting the overall environment. Interestingly, there is a notable positive trend in NDWI from 1987 to 2017 (**Figure 10B**).

CONCLUSION

In the wider context of global environmental change, consideration of the actual and potential future impacts of land-use/cover transformation is necessary. Land is a vital but limited resource and its capacity for restoration following transformation may be constrained. In analyzing diverse aspects of LULC change and its impact on the environment in the Barddhaman district, it is concluded that the western parts (Raniganj, Asansol- Durgapur industrial regions) are highly impacted by inappropriate land use practices; much of the agricultural and plantation land in these regions has been built-up for residential, commercial and industrial development.

While there are some positive indications in terms of environmental conditions in the south-eastern parts of the district, where plantations and water bodes have increased, forest cover has rapidly decreased, most notably in Kanska, Faridpur Durgapur, and Ausgram regions of the district. Built-up land has also increased substantially, effectively doubling between 1987 and 2017. There are clear signs of the deleterious impacts, especially in the increased LST values. The implications are such that the district authorities need to establish mitigation measures and raise awareness of the local people regarding land-use practices. The negative effects of LULC change on the environment manifest at site—specific level but can have implications at regional scales and beyond. Thus, the main role of the district administration and other policy making bodies is to implement evidence-based practices to transform land into a productive and sustainable system that can be effective to the future without adverse effects on environment.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://earthexplorer.usgs.gov/.

AUTHOR CONTRIBUTIONS

SR and PK: data collection and software. SR, PK, and RS: conceptualization. SR: methodology, data curation, writing data source, and methodology. SR, PK, and RC: formal analysis and writing introduction. PK and RC: investigation. SR, MM, PK, and RC: resources. SR, PK, and MM: writing results discussion and conclusion. SR and MM: referencing. MM: review and editing. PK, RS, and RC: supervision. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.