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Analyzing landscape changes and their relationship with land surface temperature and vegetation indices using remote sensing and AI techniques

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Abstract

Land use patterns and consumption occur widely due to fast industrialization and development in the previous several decades, which might lead to problems such as over-exploitation of land resources, food shortages, and pollution. Monitoring and subsequent modeling of land use land cover (LULC) changes has become critical. A study of the variations in the LULC pattern of the Baghpat District of Uttar Pradesh, India, was attempted. This study assessed spatial patterns and fluctuations in growth in the Baghpat District of Uttar Pradesh (India) from 1991 to 2021. The study also analyzed the land cover changes and their effects on land surface temperature (LST), normalized difference vegetation index (NDVI), and soil indices in the Baghpat district. Decadal land use and land cover (LULC) changes were analyzed using Multitemporal Landsat Imagery and applying the maximum likelihood classifier in ENVI (Image Processing Software). Post-classification spatial measures were used to examine changes in LULC and the spatial distribution of urban growth, as well as to identify changes using ArcMap (GIS Software) across the period. Various AI techniques were used to show the trend variation in NDVI, LST, and SAVI indices using IBM-SPSS, Microsoft Office, OriginLab, and MATLAB for the study area to comprehend the variation in the index within the given period. The findings indicated significant improvements in agriculture between 1991 and 2021 (from 58.94 to 84.79%), but significant declines in vegetation cover (from 29.53 to 1.14%). The yearly percentage growth of the parallel built-up area was 3.77%, 5.59%, 6.71%, and 6.90%, respectively. Approximately 43.85% of the increase in agricultural land between 1991 and 2021 came from the conversion of vegetation covers, which fell by 96.13%. The analysis of LST, NDVI, and SAVI data revealed a substantial negative association for all years, except a slight positive correlation. NDVI and SAVI values were highest in agricultural fields with the lowest LST values, whereas fallow land regions exhibited the reverse pattern. With the help of these findings, urban planners and designers may reduce various socio-economic and environmental consequences.

Keywords Spatio-temporal changes, Geospatial techniques, LST, NDVI, SAVI

Introduction

Land use is the most common manifestation of the connection between man and the environment. Land use is the actual usage of this biophysical cover (Cihlar and Jansen 2001), whereas land cover is the observed (bio) physical cover on the earth's surface (Gregorio et al. 2016). Land use and land cover reflect the land utilization for various purposes in the selected area. The LULC has

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a direct relationship with LST and SAVI because LULC has directly affected the LST and SAVI in the Baghpat District. LULC dynamics have undergone rapid change in recent decades. Both natural and human forces (Hassan et al. 2016) have contributed to this change in the LULC pattern. As a result of the conversion of agricultural and other natural land cover types into built-up space (Dutta et al. 2020). The vegetation cover plays a significant role in the characterizing of human activities, variations in the terrestrial ecosystem, soil ecosystems, hydrology, and regional and global climate change processes (Nasim et al. 2018). In 2013 the Intergovernmental Panel on Climate Change (IPCC) described that the rapid warming of the climate system negatively influences agricultural practices and the vegetation cover (Hussain et al. 2021; Mubeen et al. 2020). Metropolitan regions are expanding outward. Land surface temperature (LST) is commonly used to measure the intensity of the SUHI effect (Zhang and Sun 2019; Luinetl et al. 2019; Zhang 2021; Jia and Zhao 2020). Most previous studies focused on the effects of urban landscape factors on LST (Xiao et al. 2007), such as the proportion of impervious surface and vegetation, the configuration of buildings, and the urban layout. It is generally agreed that more vegetation or adding green infrastructure would lower the SUHI effectively (Zhou, et al. 2024). The cost of carrying out large-scale afforestation or building renewal on the already-existed urban landscape is usually enormous, especially in populated and facility-dense areas. Because of this, it is necessary to propose and implement more flexible and practical measures to alleviate the UHI effect. On the other hand, studies also found that the intensity of human activities cast a strong, albeit fluctuating, influence on urban LST (Liu 2024; Huanchun et al. 2020). The impact of human activities on urban LST exists in both the long-term and the short-term. Surface permeability in the study area region was assessed using the Soil Adjusted Vegetation Index (SAVI). In general, SAVI specifies coverage of vegetation and health concerning soil moisture and thus accounts for the high inconsistency of built-up and non-built-up land cover in urban areas (Son et al. 2017). In SAVI, a transformation technique is presented to minimize the effects of external factors from spectral vegetation indices. SAVI controls for the influence of soil brightness in the NDVI and reduces the brightness of soil-related noise in the coverage of vegetation estimation (Cabral, et al. 2016). Vegetation health is strongly associated with surface permeability and thus provides an essential identification of impermeable surfaces, especially in urban areas.

The RS data are the most important sources widely used for change analysis in the present years (Kumar et al. 2016; Abdo et al. 2022). Since the benefits of repetitive data acquirement, its synoptic view and digital format

suitable for handling by computer, remotely sensed data, for example, the thematic mapper (TM) and operational land imager (OLI) have become the main data causes for various change analysis applications throughout the previous year's (Huyen et al. 2016; Rizvi et al. 2021; Thakur et al. 2021). However, in semi-arid and arid environments, various satellite imagery has been applied for development, monitoring, and LULC change analysis (Chaudhuri and Mishra 2016; Yohannes et al. 2021; Zhou et al. 2021; Tariq et al. 2023). Geographic information system (GIS) methods are proficiently used to examine the effects of several reasons on LULC changes: those reasons include population density, terrain slope, proximity to roads, and contiguous land use (Roy et al. 2017; Chen et al. 2020; Fashae et al. 2020). RS data, in combination with (GIS), have been supposedly used as a compelling apparatus in quantitatively assessing urban range and signifying urban development at a usually high spatial scale (Fu et al. 2020; Govind and Ramesh 2020). The benefit of multi-measuring an extensive spatial territory, satellite remote detection sufficiently associated with improved comprehension and screen scene advancement and procedures, and appraised biophysical qualities of land surfaces (Pal and Ziaul 2017; Olorunfemi et al. 2020). The most significant driver of environmental changes worldwide is thought to be the conversion of natural land cover types into artificial land use types. Consequently, LULC studies can help with critical environmental problems (Mohamed and Worku 2019; Yuan 2008), disaster management (King et al. 2016), watersheds (Paiboonvorachat and Oyana 2011), urban and regional planning (Dutta et al. 2020; Patra et al. 2018), and UHI mitigation (Gogoi et al. 2019). Detecting change on the surface of the earth using GIS (Geographic Information System) and remotely sensed images is rapidly developing into a vital tool in managing our planet's resources.

Study area

The Baghpat District in western Uttar Pradesh is represented by the study area Hindon–Yamuna interfluvial region, which is bordered on the east by the Hindon River and on the west by the river Yamuna River. It occupies a region of approximately 1345 km² and is located between latitudes 28°47' and 29°18' N and longitudes 77°07' and 77°30' E. The study region has a subtropical environment with an annual rainfall average of roughly 500 mm (Fig. 1). Alluvium from the Quaternary underlies the region geologically. Two cycles of sedimentation serve as the representation of the Quaternary period. The older one caused older alluvium (Varanasi alluvium) to be deposited. The more recent one, dating from the Late Pleistocene to the Holocene, is known as newer alluvium (Alam and Umar 2013).

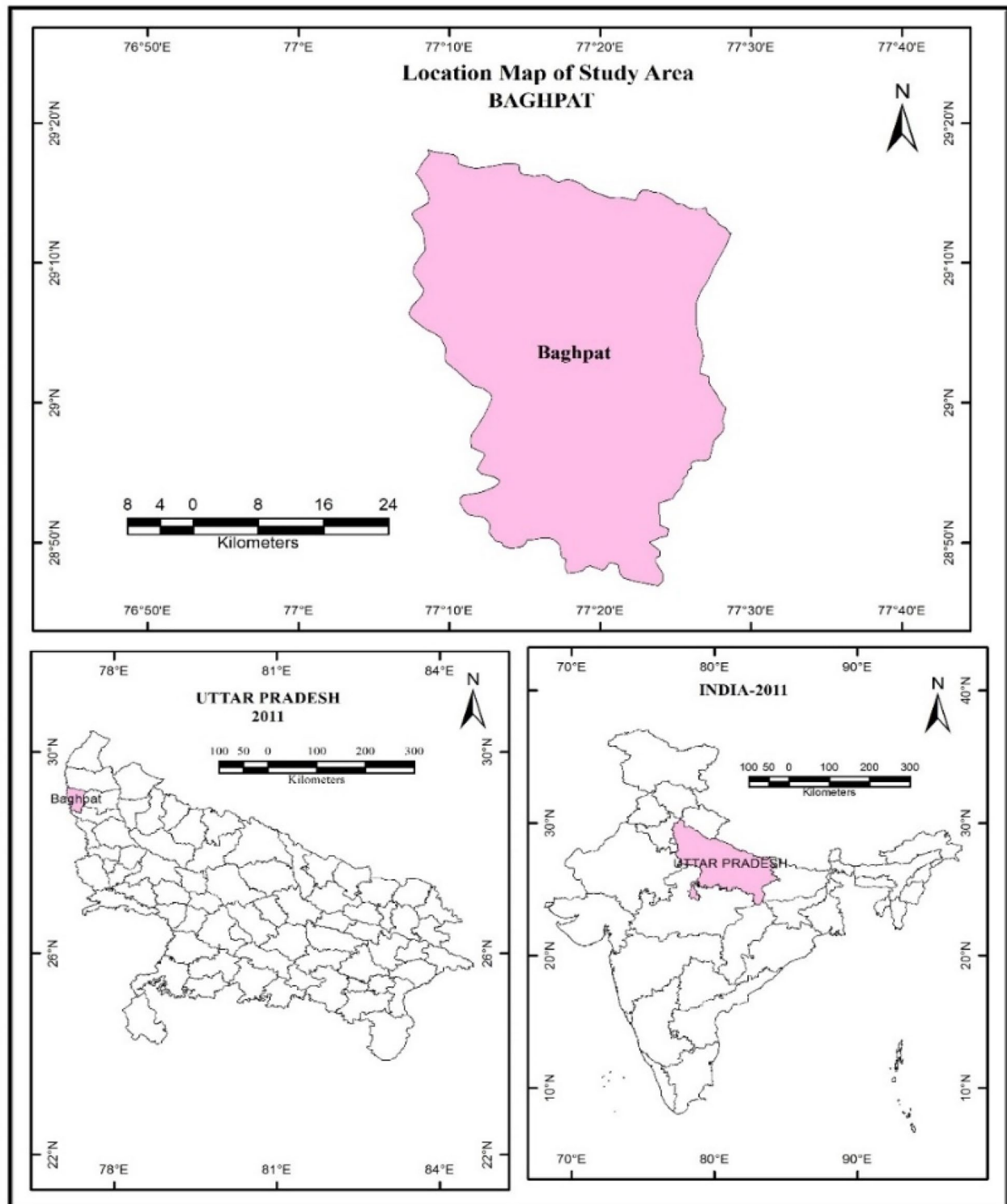


Fig. 1 Locational map of the study area. Source: prepared by authors

The majority of the land is covered with ancient alluvium, whereas fresh alluvium is only found close to the river courses. It is assumed that the Delhi rocks

underlie more than 500 m of alluvium that covers the region.

Research methodology

Remote sensing has been used widely to assess and map natural resources and other environmental issues. This study mainly focuses on the mapping of LULC changes in Baghpat district, using LANDSAT satellite data for different years with the help of GIS, recognizing the importance of LULC monitoring in the management and planning of land resources. The present research is based on a study of four decades: 1991, 2000, 2010, and 2021. There are various mapping techniques used for the assessment of the relationship between LULC and LST, SAVI, and NDVI. Show the trend variation in NDVI, LST, and SAVI indices using ArcGIS, IBM-SPSS, Microsoft Office, Origin Lab, and MATLAB for the study area to comprehend the variation in the indices within the given period. To evaluate the acquired data and assess whether there was any notable variation in the indices in the district, Pearson correlation coefficients (r) were determined and linear regression analysis was performed to investigate the relationship between the LST, NDVI, and SAVI indices. The flow diagram in Fig. 2 depicts the data and methodology procedures incorporated in land use and land cover change.

Data source

The Landsat 5 (TM) data for 1991, 2000, and 2010 and Landsat 8 (OLI/TIRS) data for 2021 were used in this study for LULC mapping and change detection analysis, and the data were retrieved from the United States Geological Survey (USGS)-Earth Explorer. The spatial resolution of the OLI/TIRS and Landsat TM data is 30 m. The following Table 1 describes the satellite data utilized in this investigation. For ground validation, samples gathered via Google Earth Pro (for 1991, 2000, 2010, and 2021) or field surveys (for 2022) were utilized to validate the LULC maps.

Data analysis

One technique for obtaining information from satellite images is LULC classification (Srivastava et al. 2012). The most popular LULC classification methods are

supervised and unsupervised classifications (Lang et al. 2008). In this study, maximum likelihood classification (MLC) was used to classify Landsat imagery (Gautam et al. 2021). Based on the NRSC level I classification method, five LULC classifications, including agriculture, water bodies, built-up areas, vegetation, and open land, were identified.

Change detection analysis

Changes are defined as changes on the surface over time in the change detection analysis. The technique for identifying changes in land use and land cover based on Landsat imagery gives an accurate and true representation of the research region. One of the most significant applications of satellite data is detecting changes in the same item throughout seasons and years. Change detection analysis is used to assess the type, extent, and pace of land cover change based on geographical and temporal variables (Rogan et al. 2006; Zubair 2006). Change detection has been calculated for the four decades 1991 to 2000; 2000 to 2010; 2010 to 2021, and overall, 1991 to 2021.

Accuracy assessment

The accuracy of classification is significant since it shows the correctness and precision of the thematic maps developed (Congalton 1988; Foody 2002; Pontius and Cheuk 2006). For the current study, accuracy is evaluated for the years 1991, 2000, 2010, and 2021. The interpretation accuracy of LULC categories identified from distant sensor data should be at least 85% (Wright and Morrice 1997; Anderson et al. 1976). Thomlinson et al. (1999) recommend that the target be an overall accuracy of 85% with no class less than 70% accuracy. In this study, accuracy was assessed using an error matrix, also known as a confusion matrix. An error matrix presents the results of a comparison of the LULC categories' reference class labels with the actual outcomes (Stehman and Czaplewski 1998). The formula for accuracy is as follows:

Kappa coefficient calculated from the following equation Eq. (1):

No. of correctly classified pixels in each category/total no. of reference pixels (the row total) * 100

$$\text{Kappacoefficient}(T) = \frac{(Ts * Tcs) - (\text{column total} * \text{row total})}{Ts^2 - (\text{column total} * \text{row total})} \times 100, \quad (1)$$

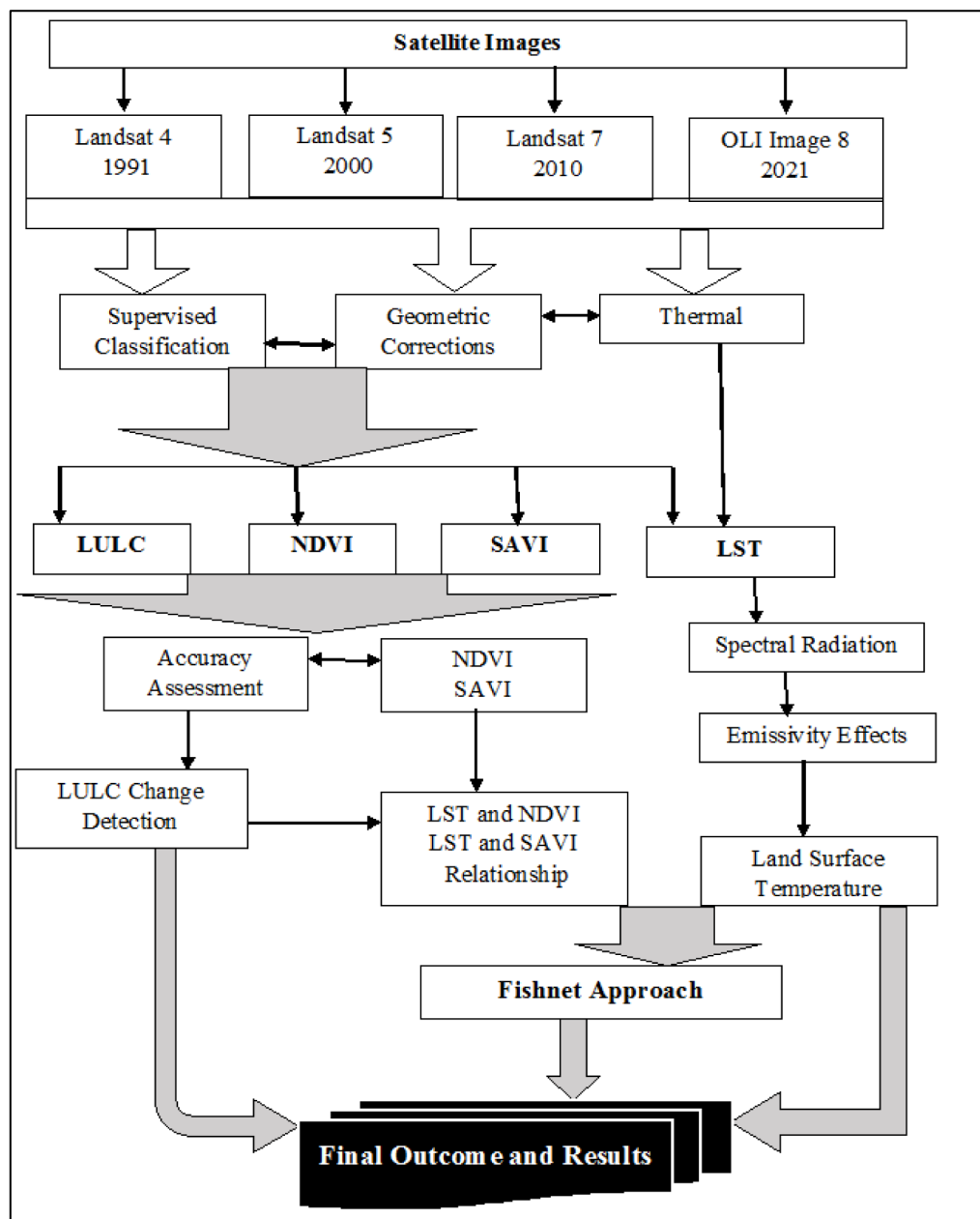


Fig. 2 Flow diagram of database and research methodology. Source: prepared by authors

where T_s = total sample and T_{cs} = total corrected sample.

Based on LULC data, the overall accuracy, producer's accuracy, user's accuracy, and overall kappa coefficient were determined using Microsoft Excel. The user's accuracy was measured by dividing the total number of pixels

in the categorized image by the number of successfully identified pixels for each LULC class. The number of accurate pixels in the categorized image for each LULC class divided by the total number of pixels in the reference data is referred to as the producer's accuracy Eq. (2).

$$\text{User accuracy} : \text{no. of correctly classified pixels in each category} / \text{total no. of reference pixels (the row total)} * 100. \quad (2)$$

$$\text{Producer accuracy} : \text{no. of correctly classified pixels in each category} / \text{total no. of reference pixels (the column total)} * 100.$$

Table 1 Technical specification of satellite images. Source: Compiled by the Authors, based on USGS data (United States Geological Survey (<https://earthexplorer.usgs.gov>))

Type				Mechanical scanner
Spatial resolution				30 m
Spectral range				0.45 μm to 12.5 μm
No. of bands				8
Temporal resolution				16 days
Year	Path and row	Spatial resolution	Description	Satellite sensor
April, 28, 1991	127/043	30 m	Landsat-5	Thematic mapper
April, 6, 2000	127/043	30 m	Landsat-5	Thematic mapper
May, 16, 2010	132/46	30 m	Landsat-7	Enhanced thematic mapper
April, 19, 2021	132/46	30 m	Landsat-8	Operational land imager (OLI)

To assess the accuracy of the results, the Kappa index was computed for the classified imagery. The Kappa coefficient represents the relative decrease of errors produced by a classification procedure when compared to the error produced by a purely random classification (Jia 2022). A Kappa score value of 1 shows perfect concurrence.

Normalized difference vegetation index (NDVI)

The NDVI value measures the degree of greenness in plants (Lo and Quattrochi 2003). These values range between -1 and $+1$, reflecting the green vegetation's uniformity. The ones around $+1$ (light hue) show a higher consistency of flora and are unique to the thick broadleaf forest. Close to -1 (black hue) represents an area with no vegetation and visible dirt or rock surface. Grasslands are connected with the 0 value (middle color). This index is calculated using the following formula Eq. (3):

$$\text{NDVI} = (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED}), \quad (3)$$

where NIR = band 4 (Landsat 5) or band 5 (Landsat 8), RED = band 3 (Landsat 5) or band 4 (Landsat 8). Eq. (4)

$$\text{In Landsat 5 : NDVI} = (\text{Band 4} - \text{Band 3}) / (\text{Band 4} + \text{Band 3}),$$

$$\text{In Landsat 8 : NDVI} = (\text{Band 5} - \text{Band 4}) / (\text{Band 5} + \text{Band 4}). \quad (4)$$

Soil adjusted vegetation index (SAVI)

SAVI is used to adjust the normalized difference vegetation index (NDVI) to account for the effects of ground brightness in sparsely vegetated areas. The SAVI derived from Landsat surface reflectance is calculated as the ratio of the R -value to the NIR value

with the surface brightness adjustment factor (L) set at 0.5 to describe most land cover types Eq. (5):

$$\text{SAVI} = \left(\frac{\text{NIR} - R}{\text{NIR} + R + L} \right) \times (1 + L), \quad (5)$$

where NIR = pixel values from the near infrared band, red = pixel values from the near red band, and L = amount of green vegetation cover Eq. (6):

$$\begin{aligned} \text{SAVI} = & ((\text{Band 5} - \text{Band 4}) / (\text{Band 5} + \text{Band 4} + 0.5)) \\ & * (1.5) \text{ in Landsat 8.} \end{aligned} \quad (6)$$

The bands that correspond to such wavelengths are known as NIR and red. The degree of green vegetation impacts the L value. $L = 1$ in areas with no green vegetation cover, $L = 0.5$ in areas with moderate green vegetation cover, and $L = 0$ in places with extremely high green vegetation cover (the NDVI method). The values returned by this index range from -1.0 to 1.0 .

Land surface temperature (LST)

The ground surface temperature measures how hot it is to the touch. Landsat dataset LST computations included the use of DN values for thermal bands and absolute radiance measurements (Ru et al. 2022).

The brightness temperature data for the atmosphere were supplied in Kelvin (K) and then converted to degrees Celsius ($^{\circ}\text{C}$), and the emissivity-corrected LST was calculated using Eq. (7):

$$\text{LST} (^{\circ}\text{C}) = \frac{T_B}{1 + \left(\frac{\lambda \times T_B}{\rho} \right) \ln \epsilon}, \quad (7)$$

where T_B = Landsat 8, 10th band brightness temperature; λ = emitted radiation wavelength

(=10.8 μm); $\rho = \frac{hc}{\sigma} (1.438 \times 10^{-2} \text{ m K})$; σ =Boltzmann constant ($1.38 \times 10^{-23} \text{ J}\cdot\text{K}^{-1}$); h =Plank's constant ($6.626 \times 10^{-34} \text{ J}\cdot\text{s}$); c =velocity of light ($2.998 \times 10^8 \text{ m}\cdot\text{s}^{-1}$); and ε is the land surface emissivity, estimated using Eq. (8):

$$\varepsilon = mP_v + n, \quad (8)$$

where $m = (\varepsilon_v - \varepsilon_s) - (1 - \varepsilon_s)F\varepsilon_v$ and $n = \varepsilon_s + (1 + \varepsilon_s)F\varepsilon_v$, where ε_v and ε_s are the vegetation and soil emissivity, respectively; the m (0.004) and n (0.986) values are taken from . P_v is the vegetation proportion and was obtained using Eq. (9):

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2, \quad (9)$$

where NDVI is the normalized difference vegetation index given by Eq. (10), derived using the surface reflectance of Landsat 8 Bands 4 (Red) and 5 (NIR):

$$NDVI = \frac{(\rho_{NIR} - \rho_{Red})}{(\rho_{NIR} + \rho_{Red})}. \quad (10)$$

Conversion of the digital number (DN) to spectral radiance (L λ)

As the temperature of an object climbs above absolute zero (K), it emits thermal electromagnetic radiation. Using this technology, the thermal sensor outputs may be converted to at-sensor radiance. The Landsat sensor gathers temperature data and stores it as a digital number (DN) ranging from 0 to 255.

The DNs are transformed to radiance values first. There are two techniques for converting DNs to radiance; the methodology chosen is decided by the scene calibration data supplied in the header file. The header file Gain and Bias (or Offset) values are employed in one way in Eq. (11), while the L MIN and LMAX spectral radiance scaling factors are used in another technique in Eq. (12):

$$L\lambda = \text{"gain"} * QCAL + \text{"offset"}, \quad (11)$$

where $L\lambda$ =At sensor radiance, gain=the slope of the radiance/DN conversion function, QCAL=digital number (DN) is the digital number of a given pixels; bias/offset= is the intercept of the radiance/DN conversion function.

Here, the spectral radiance scaling method is used because the radiance values are directly available from the header file. This is also given as:

$$L\lambda = \frac{L_{MAX} - L_{MIN}}{QCAL_{MAX} - QCAL_{MIN}} * (QCAL - QCAL_{MIN}) + L_{MIN}, \quad (12)$$

where $L\lambda$ = Spectral radiance at the sensor, LMAX = spectral radiance scaled to QCALMAX (watts/($\text{m}^2\cdot\text{sr}\cdot\mu\text{m}$)), LMIN = spectral radiance scaled to QCALMIN (watts/($\text{m}^2\cdot\text{sr}\cdot\mu\text{m}$)), QCAL = quantized calibrated pixel value in DN, QCALMAX = the maximum quantized calibrated pixel value in DN, and QCALMIN = the minimum quantized calibrated pixel value in DN.

Results and discussion

The study of land use in a specific location is a result of the natural environment and civilization working together. Knowledge of the dynamics of land use and land cover change in several dimensions on important issues and land resource planning. Remote sensing techniques have evolved into a well-known and commonly used tool for gathering data on land dynamics. Moreover, various categorization approaches have been employed to transform satellite images into an appropriate data source for land use and land cover information. For the years 1991, 2000, 2010, and 2021, the spatiotemporal pattern of Land Use and Land Cover Change has been computed.

Land use land cover change from 1991 to 2021

The study area's land use and land cover were examined in 1991, exhibiting diverse patterns and distribution across different categories. The research region has a total area of approximately 133,540.2 hectares. Water bodies occupied 0.79% (1056.06 hectares) of the total area among the various land use and land cover categories. Agriculture accounted for the majority of the land, which was 58.94% (78,705.81 hectares) (Table 2). This reflects the region's notable presence of agricultural activity. The built-up area, which included residential, commercial, and industrial projects, accounted for 3.77% of the total area (5036.22 hectares). The presence of built-up areas reflects the region's urbanization and human settlement increase. Vegetation, comprising forests, woods, and natural vegetation, covered 29.53% of the area (39,440.43 hectares). This suggests that there are significant natural ecosystems and green areas within the research region. Open land, defined as areas with little or no plant cover or specialized land use, accounted for 6.97% (9301.68 hectares) of the total area. Barren lands, fallow fields, and places experiencing land-use changes are examples of open land areas (Fig. 3).

The study region's overall area remained constant at roughly 133,540.2 hectares. Water bodies made up 0.84% (1124.91 hectares) of the total area, suggesting a modest rise over the previous decade. Agricultural activities remained to dominate land use, accounting for 74.39% of the land (99,340.99 hectares). This shows a significant growth over the past decade, indicating that agricultural

Table 2 Land use and land cover classification of Baghpat District from 1991 to 2021. Source: prepared by authors

Class/area	Area in Ha. (1991)	Area in % (1991)
Water body	1056.06	0.79
Agriculture	78,705.81	58.94
Built-up	5036.22	3.77
Vegetation	39,440.43	29.53
Open land	9301.68	6.97
Total	133,540.2	100.00
Class/area	Area in Ha. (2000)	Area in % (2000)
Water body	1124.91	0.84
Agriculture	99,340.99	74.39
Built-up	7471.13	5.59
Vegetation	5578.22	4.18
Open land	20,024.95	15.00
Total	133,540.2	100.00
Class/area	Area in Ha. (2010)	Area in % (2010)
Water body	2134.44	1.60
Agriculture	110,492.28	82.74
Built-up	8955.09	6.71
Vegetation	5671.71	4.25
Open land	6286.68	4.71
Total	133,540.2	100.00
Class/area	Area in Ha. (2021)	Area in % (2021)
Water body	1384.29	1.04
Agriculture	113,235.15	84.79
Built-up	9207.75	6.90
Vegetation	1527.48	1.14
Open land	8185.53	6.13
Total	133,540.2	100.00

practices in the region are continuing and potentially expanding. The built-up area, which included residential, commercial, and industrial projects, represented for 5.59% of the total area (7471.13 hectares).

An examination of land use and land cover in the study region in 2000 indicated significant changes compared to the preceding decade. The study region's overall area remained constant at roughly 133,540.2 hectares. Water bodies made up 0.84% (1124.91 hectares) of the total area, suggesting a modest rise over the previous decade. Agricultural activities remained to dominate land use, accounting for 74.39% of the land (99,340.99 hectares). This shows significant growth over the past decade, indicating that agricultural practices in the region are continuing and potentially expanding. The built-up area, which included residential, commercial, and industrial projects, represented 5.59% of the total area (7471.13 hectares). This demonstrates a considerable growth in built-up areas, demonstrating urbanization and human settlement

development over this period. Vegetation, encompassing forests, woodlands, and natural vegetation, occupied 4.18% (5578.22 hectares) of the land. In the Year 2010, the increasing presence of water bodies may have implications for hydrological systems, aquatic ecosystems, and overall landscape dynamics. The shifts in agriculture and built-up areas indicate the ongoing influence of human activities on land use patterns and urbanization processes. The slight increase in vegetation cover suggests potential efforts to maintain or restore natural ecosystems, which may have positive ecological implications. However, the decline in open land raises concerns about potential habitat fragmentation, loss of biodiversity, and the need for sustainable land use planning. In the year. 2021, the total area of the study region remained consistent at approximately 133,540.2 hectares. Water bodies accounted for 1.04% (1384.29 hectares) of the total area, showing a slight decrease compared with the previous

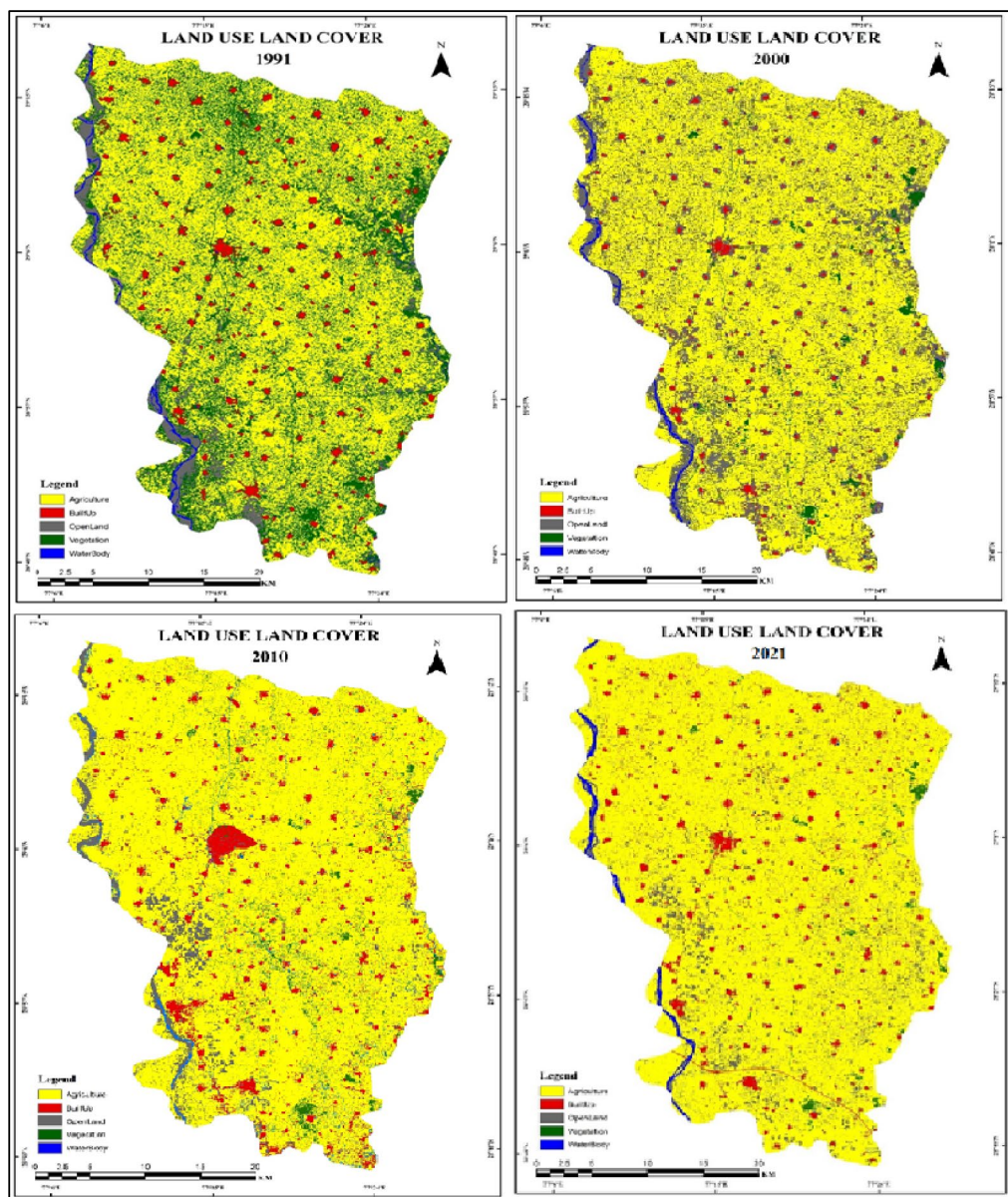


Fig. 3 Land use and land cover classification of Baghpat in 1991 to 2021. Source: prepared by authors, based on Landsat data series, 1991–2021

decade. This suggests potential changes in hydrological conditions or human interventions impacting water bodies. Agricultural activities continued to dominate the land use, covering 84.79% (113,235.15 hectares) of the land. This indicates the persistence and significance of agriculture as the primary land use in the study area. The built-up area, including residential, commercial, and industrial developments, accounted for 6.90% (9207.75 hectares) of the total area. Vegetation occupied 1.14% (1527.48 hectares) of the land, showing a slight increase compared with the previous decade. This suggests potential efforts

towards conserving or restoring natural ecosystems and green spaces.

LULC change detection

The vegetation and open land had lost most of the area during this period from 1991 to 2021, with declines of – 96.13 and – 12.00 per cent, respectively. Built-up area and agricultural land increased by more than 43.00% and 82.00% area during this period because people converted vegetation and open land to built-up and agricultural land in the outer ring of the district. The water body had increased with a good portion of their total

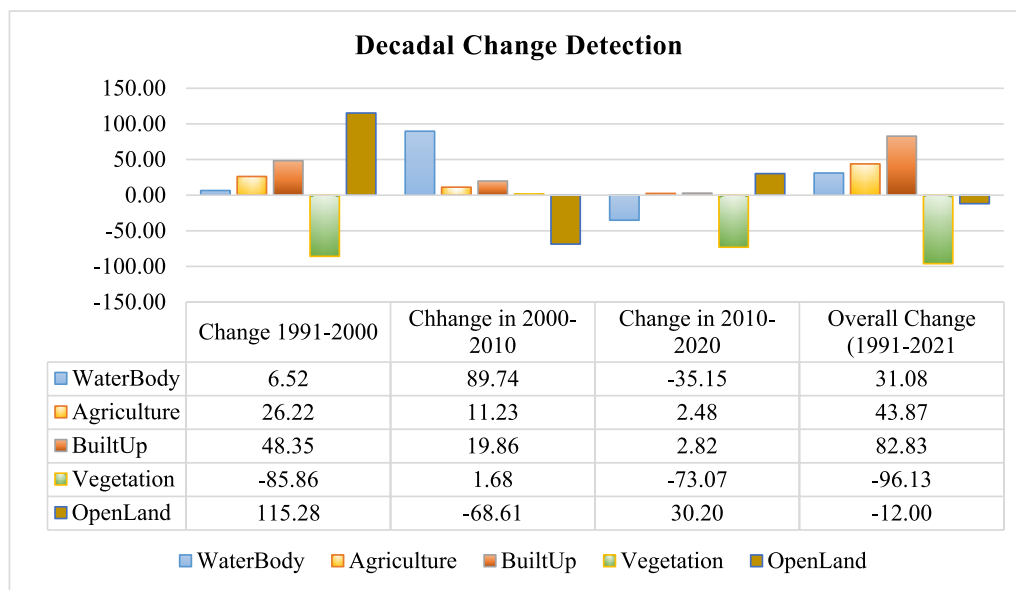


Fig. 4 Spatio-temporal decadal change detection 1991–2021. Source: calculated by authors

area with a 31.08 per cent increase. Vegetation had lost more than half of its area during this period because of the shifting in the occupation of people in the district (Fig. 4).

Accuracy assessment

The aim of accuracy evaluation is to measure the level of accuracy in categorizing pixels into different land cover types. In the research area, there were 100 pixel points (locations) used for the analysis. Accuracy evaluations were conducted for land use and land cover maps for the years 1991, 2000, 2010, and 2021 to assess the accuracy of the land use and land cover classes (Table 3). A Kappa coefficient of 1 implies perfect agreement, while a figure close to 0 suggests that the agreement is no better than that anticipated by chance.

Over a 5-year period, the classification's overall accuracy and Kappa coefficient are good. The three accuracies, Producer's Accuracy, User's Accuracy, and Overall

Accuracy, as well as the Kappa Coefficient, were determined for classification. Anderson's (1974) criterion of a minimum accuracy of 85% and Anderson et al. (1976) have been applied to any image classification. The kappa coefficient and total accuracy described map accuracy in the study area. The accuracy rates for the maps for 1991, 2000, 2010, and 2021 are 95.43, 95.63, 96.13, and 95.89, respectively.

LULC change detection matrix from 1991 to 2021

These observed land use and land cover changes reflect the dynamic nature of the study area and highlight the interplay between human activities and natural processes. The conversion of agricultural land into built-up areas suggests the expansion of urban areas, possibly driven by population growth and urbanization (Fig. 5).

The conversion of agricultural land into open land may be attributed to changes in land use practices, economic factors, or shifts in agricultural productivity. These changes can have implications for ecosystem services, biodiversity, and the availability of agricultural land (Fig. 6).

The conversion of agricultural land into natural vegetation showcases potential efforts towards environmental conservation or the implementation of land restoration programmes (Table 4). The transformations from agricultural land to water bodies may be influenced by irrigation practices, changes in water management systems, or alterations in hydrological patterns (Fig. 7).

Table 3 Overall accuracy for land use land cover classification. Source: Calculated by the Authors based on Landsat data, Landsat data series

Year	Overall accuracy (in %)	Kappa coefficient (in %)
1991	95.43	93.23
2000	95.63	94.12
2010	96.13	93.29
2021	95.89	92.96

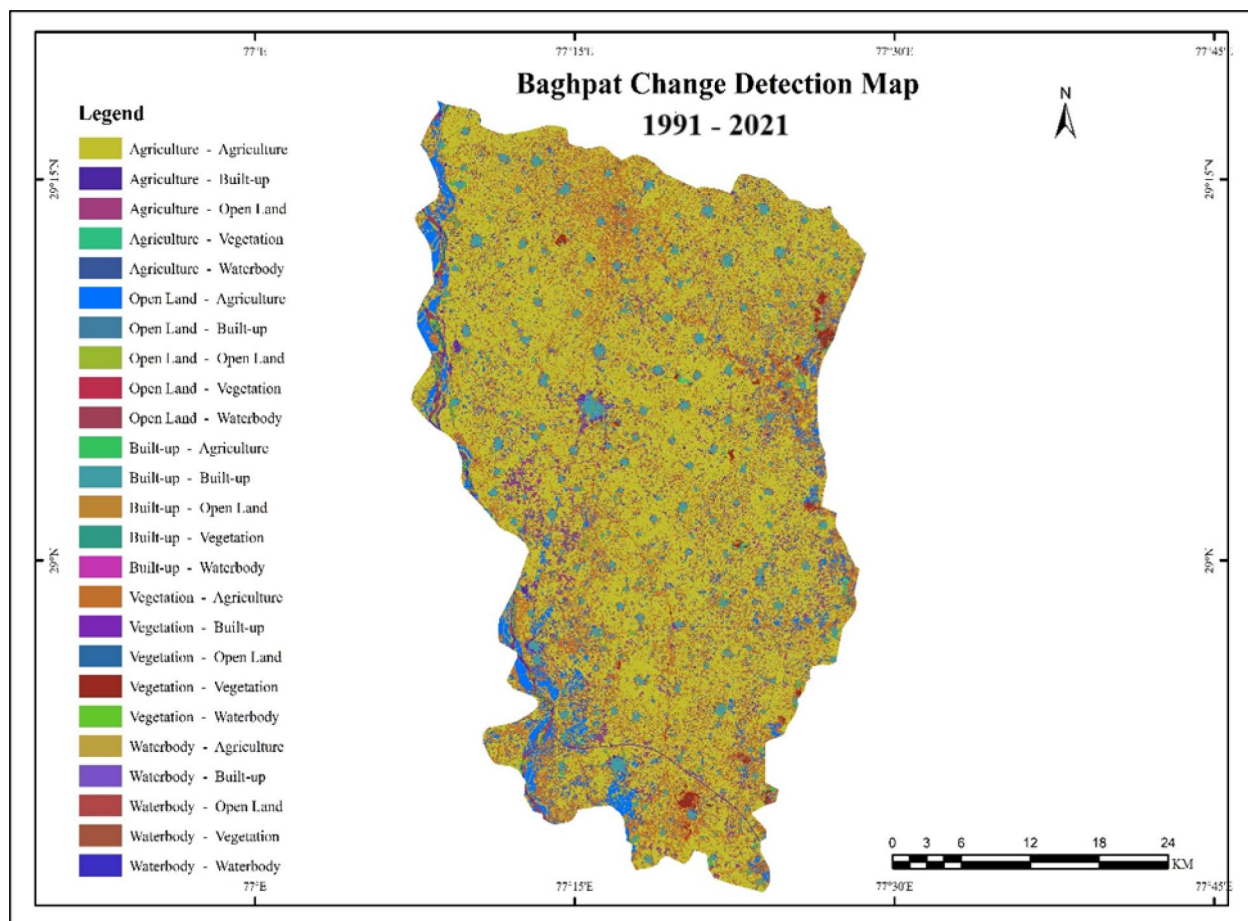


Fig. 5 LULC change detection matrix map. Source: prepared by authors, based on Landsat data series, 1991–2021

Normalized difference vegetation index (NDVI)

Normalized difference vegetation index (NDVI) measures the health of vegetation by comparing the absorption of chlorophyll in the red spectral area with the reflectance in the near-infrared spectrum. The region has seen a significant increase in healthier vegetation over the past decade (Fig. 8). Analyzing the NDVI data from 1991 to 2021 (Fig. 7) is crucial for understanding the long-term health and dynamics of vegetation in the Baghpat region. This analysis allows continuous monitoring of how vegetation is affected by environmental changes such as deforestation, urbanization, and agricultural expansion (Tables 5, 6).

The table presents the normalized difference vegetation index (NDVI) values for Baghpat from 1991 to 2021, including the minimum, maximum, and mean NDVI for each year. The mean NDVI values, indicating average vegetation health, vary over the years, showing fluctuations with periods of improvement and decline. The highest mean NDVI is observed in 1998 (0.387), while

the lowest is in 2010 (− 0.061), signifying a year of significant vegetation stress. The highest mean NDVI in 1998 reflects strong vegetation health, while 2010 stands out as a period of severe vegetation stress with a negative mean NDVI. These fluctuations demonstrate a dynamic landscape in Baghpat, characterized by both growth and decline in vegetation health. The changes likely result from environmental factors, land use changes, and climatic variations. The data emphasize the need for continuous monitoring and management efforts to sustain and improve vegetation health in the region.

In Fig. 9, there is a scatter plot with linear regression representing NDVI (normalized difference vegetation index) values over a time series analysis from 1991 to 2021. The scatter plot displays three sets of data points that correspond to the minimum, mean, and maximum NDVI values, each represented by a distinct color: red for minimum, green for mean, and blue for maximum. The scatter plot provides a visual summary of these trends,

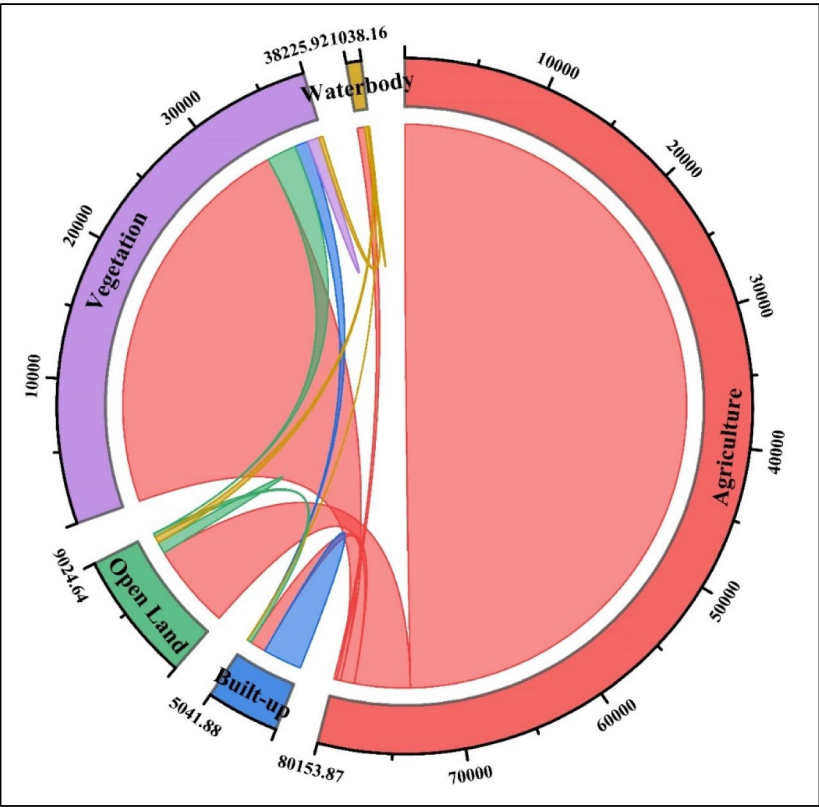


Fig. 6 LULC conversion matrix from 1991 to 2021. Source: prepared by authors

Table 4 LULC conversion matrix from 1991 to 2021. Source: calculated by authors

Classes	2021				
	Agriculture	Built-up	Open land	Vegetation	Water body
1991					
Agriculture	73,675.75	1185.19	4726.32	358.47	208.14
Built-up	1360.77	3307.37	349.06	5.52	19.16
Open land	7193.75	283.14	984.19	28.52	535.04
Vegetation	33,249.11	1148.88	2484.11	997.14	346.68
Water body	632.56	12.61	119.51	18.41	255.07

while the table offers detailed numerical data supporting the trends observed in the plot.

Soil adjusted vegetation index (SAVI)

SAVI is used to adjust the normalized difference vegetation index (NDVI) to account for the effects of ground brightness in sparsely vegetated areas. The index was

created to compensate for excessive soil reflectance in dry areas (Fig. 10). Its value varies from 0 (very high vegetation cover) to 1 (extremely low vegetation cover).

The index was created to compensate for excessive soil reflectance in dry areas. Its value varies from 0 (very high vegetation cover) to 1 (extremely low vegetation cover). The SAVI range is also given by Ghebregabher et al.

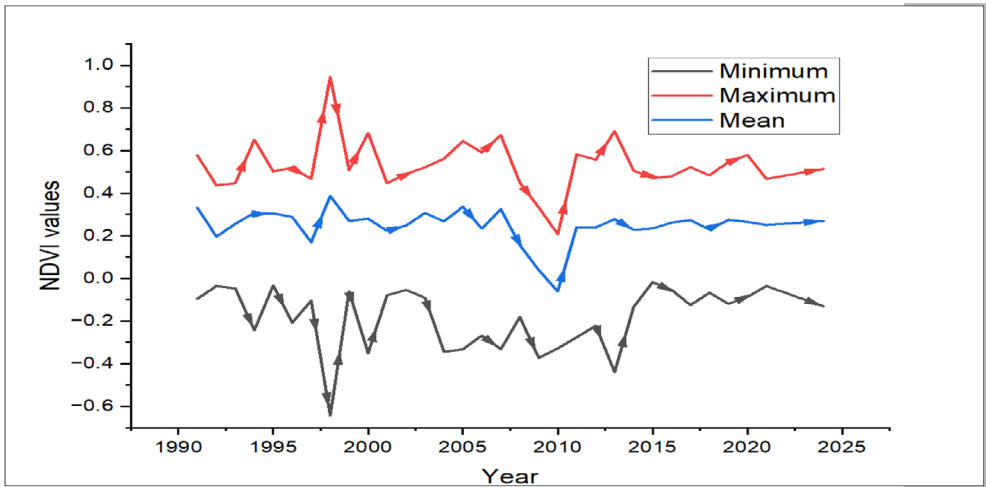


Fig. 7 Trend analysis of NDVI 1991–2021. Source: prepared by authors

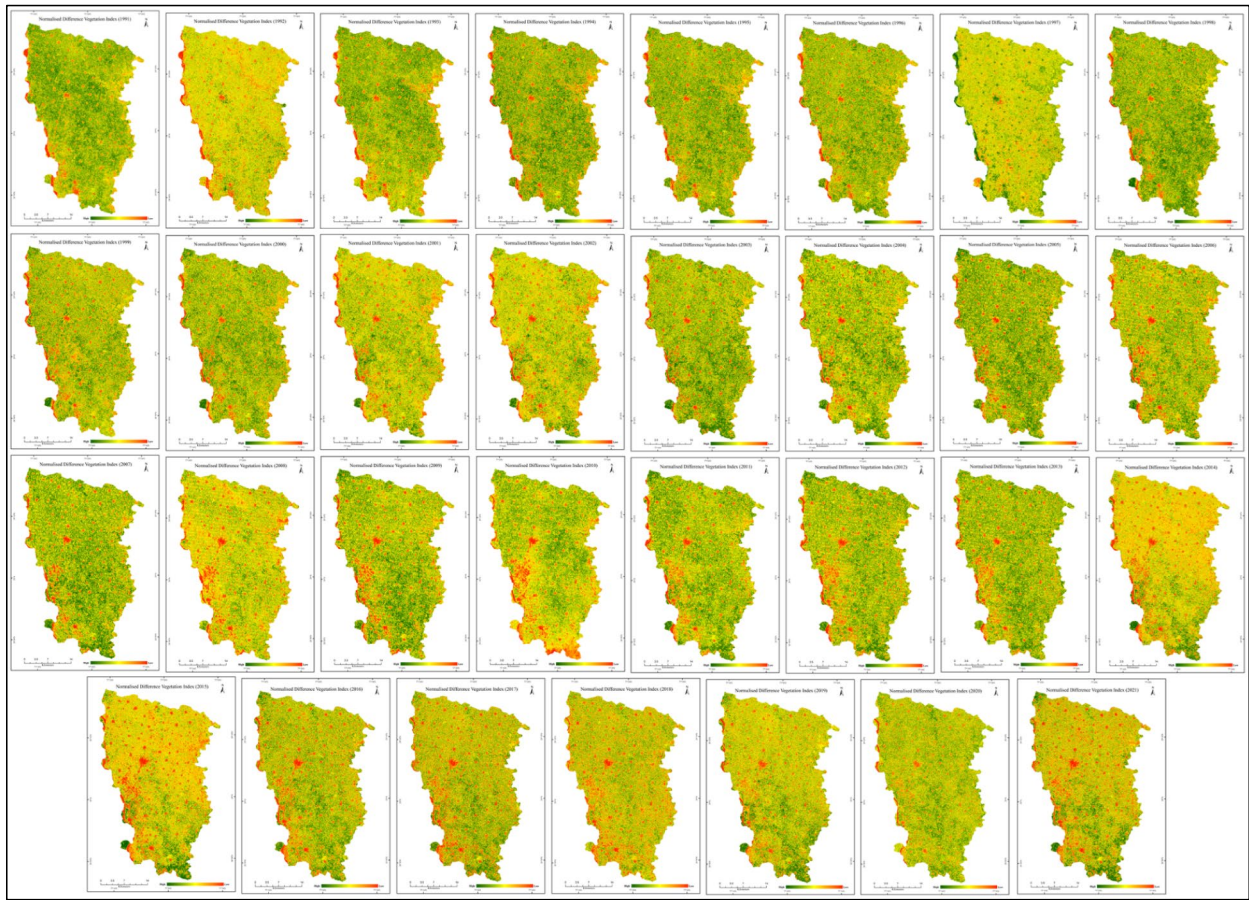


Fig. 8 Trend of spatio-temporal distribution of NDVI 1991–2021. Source: prepared by authors, based on Landsat data series, 1991–2021

(2016), with +1 signifying good vegetation cover and lower values denoting stressed vegetation.

The background soil conditions have a significant impact on canopy section spectra and listed vegetation indices. Many studies have found that for a given number

Table 5 Trend of normalized difference vegetation index, 1991–2021. Source: calculated by authors, based on Landsat data series, 1991–2021

Year	Minimum	Maximum	Mean
1991	− 0.096	0.577	0.332
1992	− 0.036	0.437	0.196
1993	− 0.047	0.447	0.256
1994	− 0.243	0.651	0.308
1995	− 0.033	0.502	0.305
1996	− 0.208	0.52	0.288
1997	− 0.104	0.467	0.17
1998	− 0.644	0.945	0.387
1999	− 0.062	0.508	0.27
2000	− 0.35	0.682	0.28
2001	− 0.079	0.447	0.223
2002	− 0.054	0.49	0.248
2003	− 0.091	0.521	0.307
2004	− 0.344	0.562	0.267
2005	− 0.333	0.644	0.336
2006	− 0.268	0.591	0.233
2007	− 0.333	0.672	0.325
2008	− 0.181	0.449	0.156
2009	− 0.373	0.333	0.039
2010	− 0.328	0.207	− 0.061
2011	− 0.276	0.582	0.241
2012	− 0.222	0.557	0.239
2013	− 0.439	0.69	0.278
2014	− 0.134	0.506	0.228
2015	− 0.018	0.47	0.234
2016	− 0.054	0.479	0.262
2017	− 0.125	0.522	0.273
2018	− 0.067	0.483	0.229
2019	− 0.12	0.547	0.275
2020	− 0.087	0.579	0.265
2021	− 0.036	0.467	0.251

Table 6 Trend of soil adjusted vegetation index, 1991–2021. Source: calculated by authors, based on Landsat data series, 1991–2021

Soil adjusted vegetation index			
Year	Minimum (temperature °C)	Maximum minimum (temperature °C)	Mean minimum (temperature °C)
1991	− 0.04	0.28	0.16
2000	− 0.25	0.28	0.04
2010	− 0.09	0.32	0.1
2021	− 0.06	0.35	0.15

of plants, black soil substrates result in better agricultural yields (Huete 1988). In 2021, the greatest SAVI in the research region was 0.35. In 1991, the minimum SAVI in the research region was − 0.25. Between 1991 and 2021, the average SAVI value varied from 0.04 to 0.16.

Land surface temperature (LST)

Landsat dataset LST computations included the use of DN values for thermal bands and absolute radiance measurements (Nasir et al. 2022; Ru et al. 2022). The datasets were pre-processed in order to correct the pre-launch calibration constants and the assumption of radiance values with unity emissivity.

Landsat 8 images from the 10th band were used to construct LST maps in this investigation (Fig. 11). The datasets were pre-processed in order to correct the pre-launch calibration constants and the assumption of radiance values with unity emissivity. Landsat 8 images from the 10th band were used to construct LST maps in this investigation.

The LST of the Baghpat district changed dramatically between 1991 and 2021. The majority of the high LST values are located around the district's aiming range and other urban areas, whereas low values are found near vegetated areas and water bodies. The lowest temperature increased from 17.47 degrees Celsius in 1991 to 18.38 degrees Celsius in 2021, while the maximum temperature increased from 28.76 degrees Celsius in 1991 to 29.52 degrees Celsius in 2021. The mean temperature in 1991 was 19.89 °C with a standard deviation of 1.13 °C, whereas the mean temperature in 2021 is 22.51 °C with a standard deviation of 0.94 °C (Table 7). The average LST temperature has risen by 2.62 degrees Celsius.

Relationship between NDVI, LST and SAVI

The fishnet approach was used to build a relationship using pixel values from the land surface temperature (LST), normalised difference vegetation index (NDVI), and soil adjusted vegetation index (NDVI). The fishnet tool creates a feature class using a net of rectangular cells. The three key pieces of information required to produce a fishnet are the fishnet's spatial area, the number of rows and columns, and the degree of rotation. Karl Pearson's coefficient of correlation was used to evaluate the relationship between LST, NDVI, and SAVI. LST was treated as an independent variable in this calculation, while NDVI and SAVI were treated as dependent variables. Figures 12 and 13 show that the trend over time is towards higher NDVI and somewhat lower LST. It was also shown that as agricultural fields drifted westward over time, LST reduced and NDVI increased. This implies that increased plant cover leads to higher NDVI and lower LST, and vice

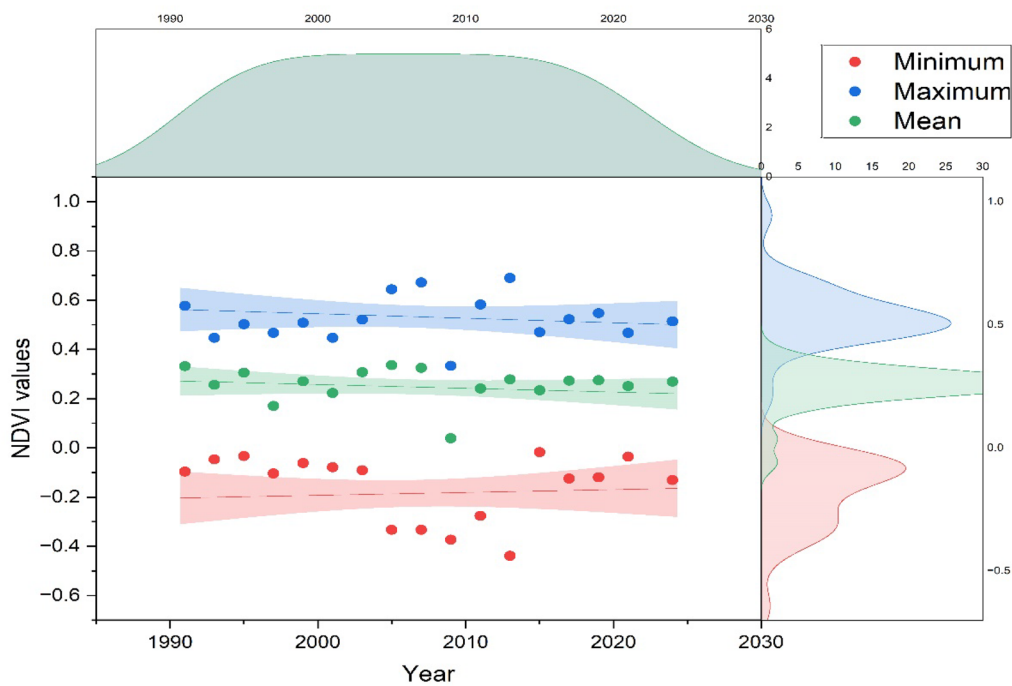


Fig. 9 Scatter plot with linear regression of NDVI 1991–2021. Source: prepared by authors

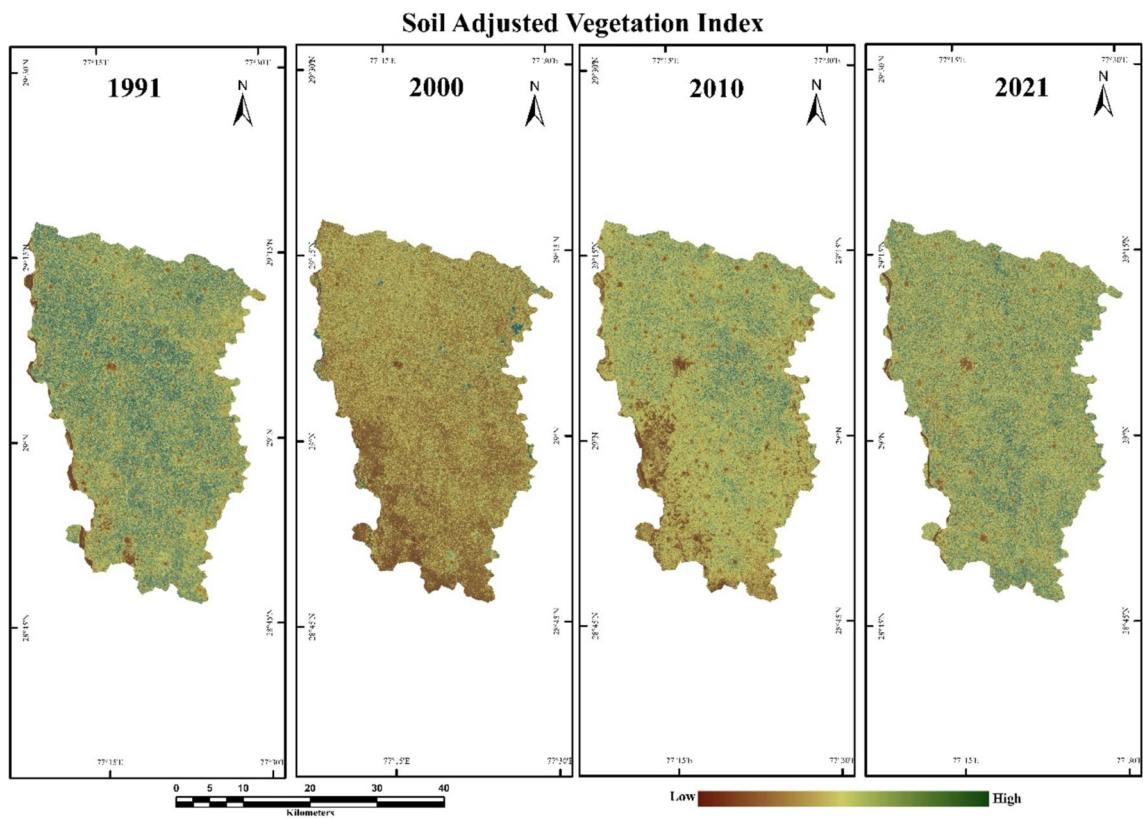


Fig. 10 Trend of spatial distribution of SAVI 1991–2021. Source: prepared by authors, based on Landsat data series, 1991–2021

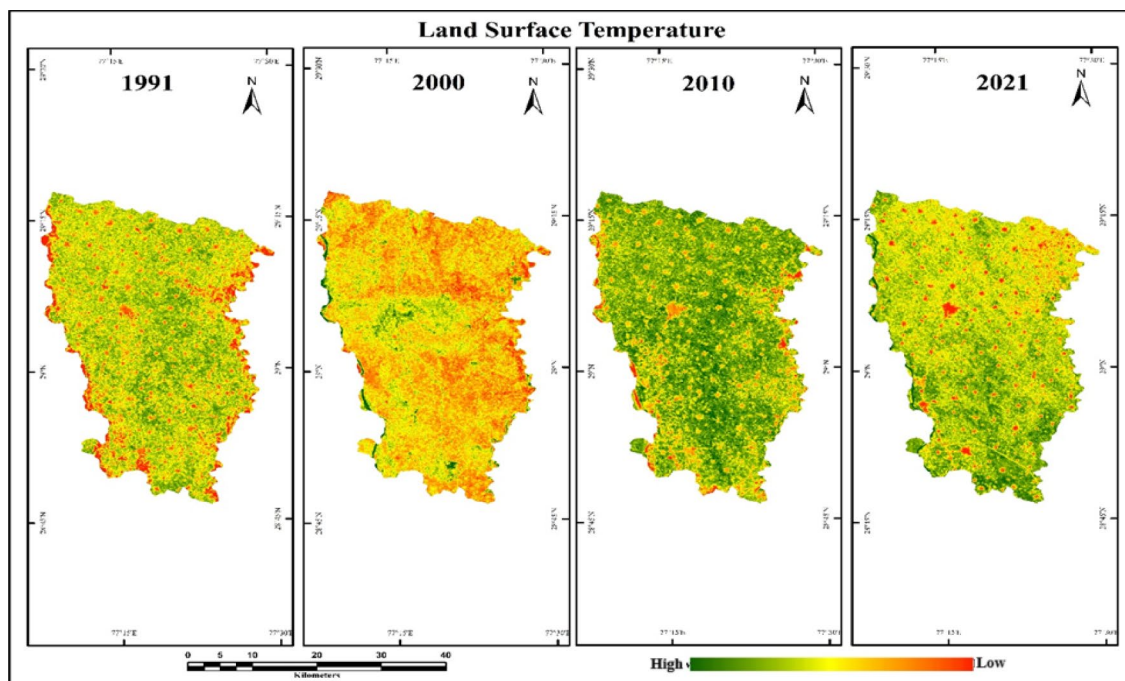


Fig. 11 Trend of spatial variation in land surface temperature in Baghpur District, 1991–2021. Source: prepared by authors, based on Landsat data series, 1991–2021

Table 7 Trend of spatial distribution of land surface temperature, 1991–2021. Source: calculated by authors, based on Landsat data series, 1991–2021

Year	Minimum (temperature in °C)	Maximum (temperature °C)	Mean (temperature °C)	Std. deviation
1991	17.47	28.76	19.89	1.13
2000	23.25	37.22	31.53	1.27
2010	26.67	45.56	31.7	2.04
2021	18.32	29.52	22.51	0.94

versa, where LST is negatively related to NDVI and vegetation cover.

To calculate the Pearson correlation of LST with NDVI and SAVI, 1581 random sample sites were taken over the study area. LST has a negative association with NDVI, according to Pearson correlation data. ($r = -0.669$, $P < 0.5$ in 1991 & $r = -0.361$, $P < 0.5$ in 2018) (Figs. 10, 12, 13). However, whereas the LST and SAVI have a positive connection in 1991 ($r = 0.00$, $P < 0.5$ in 1991 and $r = -0.21$, $P < 0.5$ in 2021), they have an adverse relationship in 2021 (Tables 8, 9).

Furthermore, all of the correlation coefficients are significant at the 0.01 level (2-tailed). As a result, it suggests that built-up areas will increase LST, whereas greenery will decrease it. R values greater than 95% for all time periods suggest a significant negative association between LST and NDVI.

Scatter plots with linear regression demonstrated a negative relationship between vegetation and soil

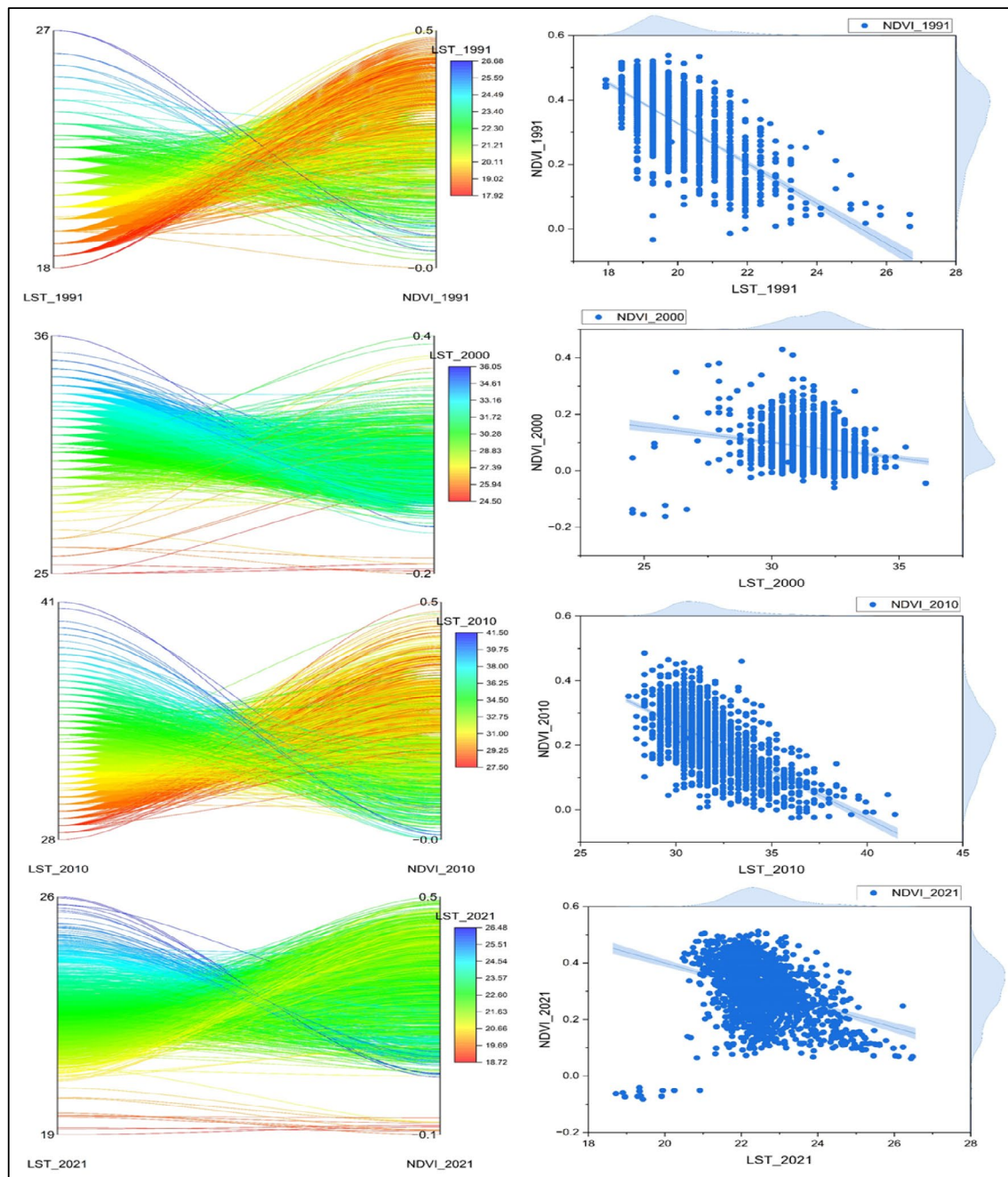


Fig. 12 Scatter plots with linear regression and trend of correlations between LST with NDVI, 1991 to 2021. Source: prepared by authors

indices and LST (Figs. 10 and 11). LST levels are low as long as vegetation biophysical parameters are high. Furthermore, the biophysical indicators may be well described by the LST. To some degree, the vegetation indices collectively indicate land use aspects, whereas the LSTs coherently reflect the temperature of the land surface. As a result, combining LST with NDVI and SAVI at appropriate intervals may yield some

interesting results. Our study supports this hypothesis using an interval of 0.01 for the vegetation indices and a mean value of LST for the relevant pixels.

Implications of LULC and vegetation indices

The interaction between land surface temperature (LST) and vegetation has significant implications for agriculture, including productivity, sustainability, and

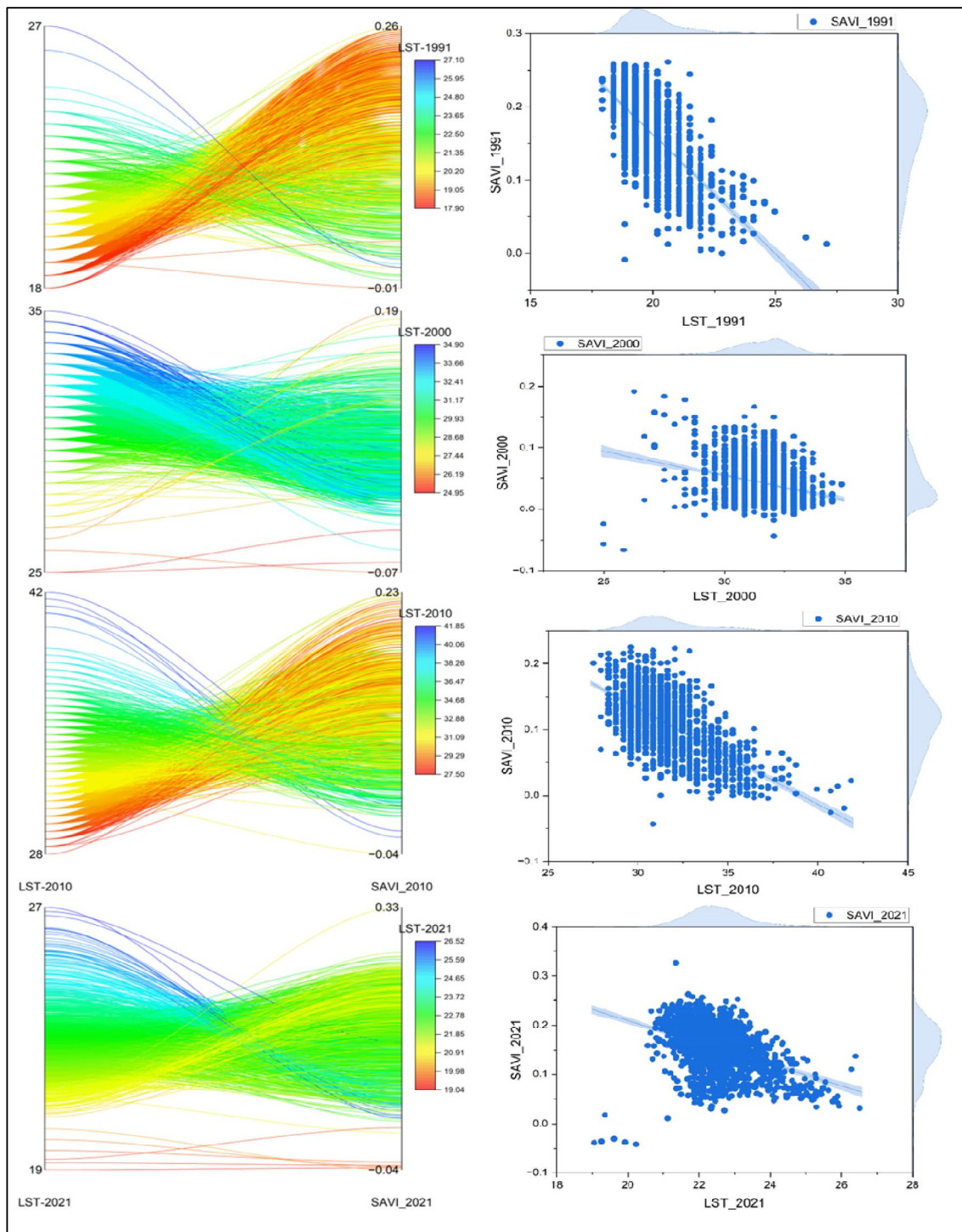


Fig. 13 Scatter plots with linear regression and trend of correlations between LST with SAVI, 1991 to 2021. Source: prepared by authors

adaptation. Changes in the landscape, such as deforestation or natural processes like desertification, affect land suitability for different crops. Vegetation plays a crucial role in regulating water cycles, affecting

evapotranspiration rates, soil moisture levels, and water runoff patterns. Understanding the relationship between LST and vegetation is important for managing water resources and determining suitable irrigation

Table 8 Descriptive statistics of Pearson correlation of LST with NDVI and SAVI for the year 1991

NDVI and LST-1991	NDVI	LST	SAVI and LST-1991	SAVI	LST
NDVI			SAVI		
Pearson correlation	1	− 0.669**		1	0.010**
Sig. (2-tailed)		0.000			0.691
N	1581	1581		1581	1581
LST			LST		
Pearson correlation	− 0.669**	1		0.010**	1
Sig. (2-tailed)	0.000			0.691	
N	1581	1581		1581	1581

** Correlation is significant at the 0.01 level (2-tailed)

Table 9 Descriptive statistics of Pearson correlation of LST with NDVI and SAVI for the year 2021

NDVI and LST-2021	NDVI	LST	SAVI and LST-2021	SAVI	LST
NDVI			SAVI		
Pearson correlation	1	− 0.361**		1	− 0.021**
Sig. (2-tailed)		0.000			.403
N	1581	1581		1581	1581
LST			LST		
Pearson correlation	− 0.361**	1		− 0.21**	1
Sig. (2-tailed)	0.000			0.403	
N	1581	1581		1581	1581

** Correlation is significant at the 0.01 level (2-tailed)

solutions in agricultural landscapes. Integrating remote sensing technologies, GIS, and climate modeling can help stakeholders understand the complex interactions between landscape dynamics, LST, and vegetation cover, leading to informed strategies for improving agricultural sustainability and productivity.

Conclusion

In conclusion, Baghpat is an agricultural district with an area of 109,000 hectares, and the majority of its population resides in rural areas. Small and marginal farmers cultivate a significant portion of agricultural land. Over the past decade, there has been a slight decrease in agricultural land, leading to reduced soil productivity, water quality, and soil nutrients. While there have been improvements in agriculture, there has been a significant decline in vegetation cover. The conversion of vegetation covers accounted for a substantial portion of the increase in agricultural land, leading to a decrease in vegetation covers.

Remote sensing-based vegetation indices are useful for monitoring crop growth and drought on a large scale, emphasizing the importance of understanding land cover and vegetation indices in rural–urban landscapes.

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Author contributions

Mr. Harish Kumar conceived and designed the research paper, collected and processed the data, and wrote the original draft. Prof. Subhash Anand supervised the study, provided critical feedback on the study design, data interpretation, and contributed to manuscript writing. Dr. Pankaj Kumar assisted in data analysis, reviewed the literature, and contributed to manuscript preparation. Dr. Manish Kumar contributed to the conceptualization of the study, literature review, and manuscript editing.

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Availability of data and materials

The data used in this study, including satellite imagery and vegetation indices, are publicly available and were acquired from the United States Geological Survey (USGS) and Earth Explorer for Landsat imagery. The processed data, results, and relevant materials generated during the study are available from the corresponding author upon reasonable request. All software tools used in this research, such as ENVI, ArcMap, and SPSS, are either open source or commercially licensed to the research institution. Data sharing complies with institutional and ethical guidelines, and any supplementary datasets will be provided upon request, subject to proper usage agreements.

Declarations

Competing interests

The authors declare that they have no competing interests regarding the content and findings presented in this manuscript. All authors have approved the final version of the manuscript and agree with its submission to the journal. There are no financial, personal, or professional conflicts that could influence the research outcomes.

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