

SPATIAL–TEMPORAL DYNAMICS OF LAND SURFACE TEMPERATURE IN RELATION TO FRACTIONAL VEGETATION COVER AND LAND USE/COVER IN THE KAMRUP DISTRICT, ASSAM.

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Abstract : An important biophysical indicator of surface energy balance, land-atmosphere interactions, and the thermal response of microclimates to changes in land use and land cover (LULC) is land surface temperature (LST). Understanding the reciprocal relationship between the environment and landscape management requires evaluating the spatiotemporal dynamics of LST in connection to vegetation change. Over the first two decades of the twenty-first century (2000–2020), this study examines the long-term fluctuation of LST and Normalized Difference Vegetation Index (NDVI) in Kamrup district, Assam, India. LST and NDVI for the pre-monsoon (March) and post-monsoon (October/November) seasons were derived from multi-temporal Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS imagery, while LULC was categorized into six major categories using supervised maximum likelihood classification and verified through accuracy assessment. The findings show that the LULC classification achieved good reliability, with a Kappa coefficient of 0.88 and an overall classification accuracy of above 90%. During the same time period, settlement and barren land increased significantly, especially in the Brahmaputra River corridor, while agricultural land dropped by 10%. Compared to the post-monsoon season, the maximum pre-monsoon LST rose by 11.6 °C, a significantly higher increase. A substantial inverse association between NDVI and LST was also found by statistical analysis, which confirmed that places with dense vegetation consistently had lower surface temperatures while the conversion of vegetated landscapes into built-up and barren surfaces increased thermal conditions. Overall, the results show that increasing surface temperatures in Kamrup district have been mostly caused by progressive LULC transition, especially plant loss. This study's methodological framework offers a reliable and affordable way to monitor the dynamics of thermal landscapes over an extended period of time. It also provides important scientific evidence to support strategies for climate adaptation, sustainable land-use planning, and regional environmental management.

Keywords: Land Surface Temperature; NDVI; LULC change; Landsat; Kamrup; Assam

I. INTRODUCTION

1.1 Background

Rising land surface temperatures are one of the most prominent local indicators of global climate change, and they are intimately linked to the loss of vegetated and pervious surfaces as landscapes urbanize. LST is the radiative skin temperature of the land surface determined by a satellite thermal sensor. It is widely used in scientific communities because it directly reflects the balance of incoming solar radiation, surface emissivity, and the evapotranspirative cooling provided by vegetation and water bodies (Kerr et al., 2000; Feizizadeh et al., 2013). Sustained LST increases have immediate effects, such as reduced agriculture, greater fire risk, and decreased reservoir and river levels, along with indirect socioeconomic consequences, such as lower farm production, elevated food costs, and rural out-migration (IPCC, 2007, 2014).

Remote sensing and GIS have emerged as the primary techniques for monitoring LST at the regional scale due to their potential to provide reliable, spatially continuous monitoring without the need for dense ground station networks. During multi-decadal change detection, the Landsat program in particular contains a continuous, moderate-resolution (30 m optical/60–120 m thermal) record dating back to the 1970s (Markham, 2013). The Normalized Difference Vegetation Index (NDVI), a spectral index derived from the red and near-infrared bands that measures vegetation greenness and abundance, is frequently analysed in conjunction with LST because it is highly influenced by the type and density of vegetation cover (Dymond et al., 1992; Small & Wu, 2006).

1.2 The Bilateral relationship between LST & NDVI

A significant body of work across tropical and subtropical urban and peri-urban landscapes has documented an adverse correlation between LST and NDVI: the lowest surface temperatures are generally found over dense vegetation and water, and the highest over bare, sandy, or built-up land (Yuan & Bauer, 2007; Weng et al., 2004; Joshi & Bhatt, 2012). It is well known that the strength of this relationship differs depending on the type of land cover, the season, and geography. According to several studies, there is a weaker negative correlation over already-bare or impervious surfaces and a stronger one during wetter seasons, when moisture and canopy cover are at their highest (Ibrahim, 2017; Feng et al., 2019). Comparable Landsat-based studies in South and Southeast Asian cities, such as Vadodara (Joshi & Bhatt, 2012), Sikkim (Lal et al., 2019), and Guwahati (Talukdar, 2020), the latter being the city immediately adjacent to the current study area, provide a regional context for reading the Kamrup findings.

1.3 Objectives

Assam's Kamrup district, which is situated on the Brahmaputra River's floodplain, combines rapid, riverbank-oriented population expansion with a sprawling agricultural and forest landscape. The district's vegetative cover has been declining over the past few decades primarily because of deforestation, land degradation bringing on by floods and erosion, and expanding low-density settlement; however, the impact on surface temperature has not yet been measured over a multi-decadal Landsat time series unique to this district.

- (i) Estimate the change in LST over Kamrup district during the pre-monsoon and post-monsoon seasons between 2000 and 2020;
- (ii) Calculate the corresponding change in vegetation cover (NDVI) during the same time period and seasons;
- (iii) Determine the statistical correlation between LST and NDVI for each season and year.

2. STUDY AREA

Kamrup Metropolitan districts to the east, Baksa district to the north, Nalbari, Barpeta, and Goalpara districts to the west, and the state of Meghalaya to the south encircle Kamrup district, an administrative district in Assam, India. It is between 25°46'–26°49' N and 90°48'–91°50' E, encompassing an area of around 3,105 km². In 2003, Kamrup district was created as the previously undivided Kamrup district was split into Kamrup and Kamrup Metropolitan districts. The district is divided into two distinct physiographic regions by the Brahmaputra River: a northern alluvial plain with agricultural landscapes around Rangia, Koya, Kamalpur, and North Guwahati, and a southern zone with dense forest cover surrounded by the foothills of the Meghalaya Plateau. The district is particularly vulnerable to frequent flooding, erosion, and seasonal sand deposition due to its vast riverine network, low-lying floodplains, and alluvial deposits. These geomorphic and hydrological processes have a substantial impact on land use and land cover dynamics, vegetation distribution, and surface energy balance, influencing the spatial and temporal variability of land surface temperature spread throughout the district.

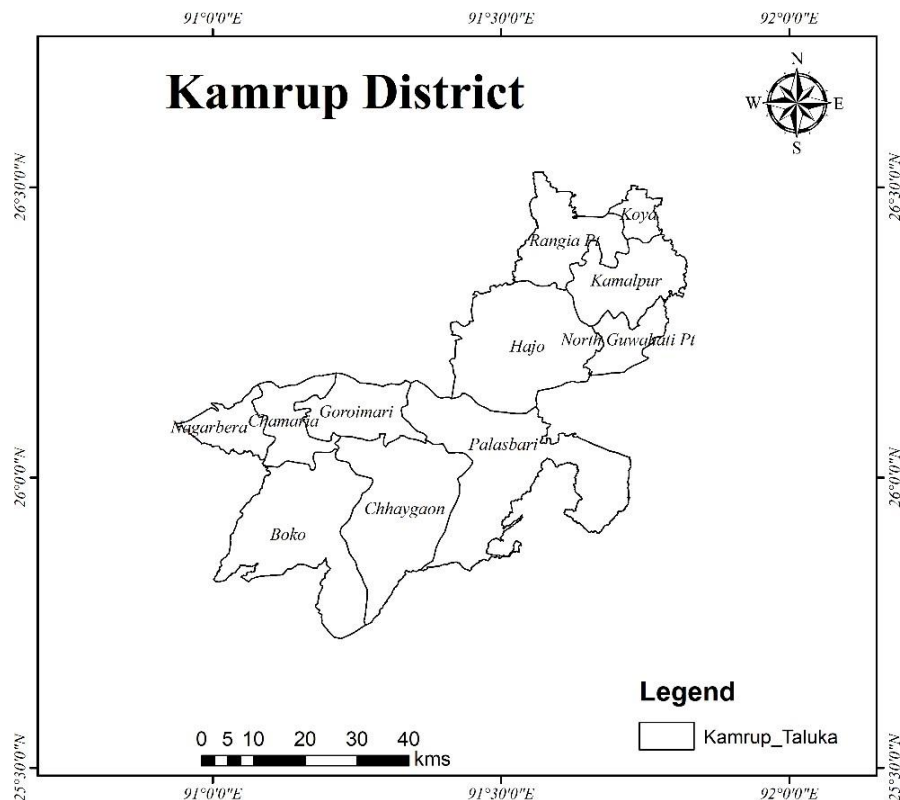


Figure 1 :- Location of Kamrup district, Assam, showing constituent taluka boundaries.

3. Data and Methodology

3.1 Satellite data

Cloud-free Landsat imagery for Path/Row 137/042 was extracted for three reference years (2000, 2010, and 2020) over the course of the pre-monsoon (March) and post-monsoon (October/November) seasons. Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) are only a few of the Landsat missions that are present in this two-decade dataset (Table 1). The utilization of cloud-free images from identical seasonal windows ensures temporal consistency while eliminating atmospheric and phenological variability, allowing for valid long-term assessments of land surface temperature, vegetation dynamics, and land use/land cover patterns.

Table 1: - Satellite imagery used for LST, NDVI, and LULC derivation

Date of Acquisition	Local Time	Season	Satellite / Sensor	Path/Row
20 Mar 2000	03:57	Pre-monsoon	Landsat 5 (TM)	137/042
02 Nov 2000	04:02	Post-monsoon	Landsat 5 (TM)	137/042
21 Mar 2010	04:16	Pre-monsoon	Landsat 7 (ETM+)	137/042
06 Nov 2010	04:19	Post-monsoon	Landsat 7 (ETM+)	137/042
30 Mar 2020	04:23	Pre-monsoon	Landsat 8 (OLI/TIRS)	137/042
25 Oct 2020	04:24	Post-monsoon	Landsat 8 (OLI/TIRS)	137/042

3.2 Image pre-processing

Image preprocessing and geographical analysis were carried out using ArcGIS 10.8 (ArcMap) and QGIS 3.16. In order to generate analysis-ready datasets for further geospatial analysis, the acquired Landsat imagery was subjected to standardized preprocessing techniques such as radiometric calibration, geometry correction, and cloud masking (Markham, 2013). Using QGIS 3.16's Fill NoData tool, the Landsat 7 ETM+ (2010) imagery was further adjusted to remove scan line corrector (SLC)-off striping effects, enhancing spatial continuity and data quality. The Landsat 7 ETM+ (2010) imagery was further corrected to eliminate scan line corrector (SLC)-off striping effects using the Fill NoData tool in QGIS 3.16, thereby improving spatial continuity and data

quality. Subsequently, all images were clipped to the Kamrup district boundary using the Extract by Mask tool. To ensure spatial consistency across all datasets, the thermal infrared bands were resampled to match the spatial resolution of the optical bands prior to land surface temperature (LST) retrieval. ArcGIS 10.8 was further employed for raster algebra-based computation of the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), supervised maximum likelihood classification of land use/land cover (LULC), raster reclassification, and statistical analyses of the LST–NDVI relationship.

3.3 Land Surface Temperature (LST) retrieval

Land Surface Temperature (LST) was determined using Landsat imagery's thermal infrared bands, notably Band 6 for Landsat 5 TM and Landsat 7 ETM+ and Band 10 for Landsat 8 OLI/TIRS. The retrieval procedure followed the standard radiometric conversion approach frequently utilized in Landsat-based thermal remote sensing studies, which involved sequentially converting digital numbers (DN) to top-of-atmosphere (TOA) spectral radiance, brightness temperature (BT), land surface emissivity (LSE), and finally land surface temperature (LST) (Qin et al., 2001; Bendib et al., 2016).

Initially, the digital number (DN) values of the thermal bands were transformed to top-of-atmosphere (TOA) spectral radiance using the radiometric rescaling parameters provided in the image metadata, according to the following equation:

$$L\lambda = ML \cdot Q_{cal} + AL$$

where $L\lambda$ is TOA spectral radiance ($W\ m^{-2}\ sr^{-1}\ \mu m^{-1}$), ML and AL are the band-specific radiance rescaling coefficients from the scene metadata, and Q_{cal} is the quantized calibrated pixel value (DN).

TOA spectral radiance was then converted to TOA brightness temperature:

$$BT = K2 / \ln(K1 / L\lambda + 1) - 273.15$$

where BT is brightness temperature ($^{\circ}C$) and $K1$, $K2$ are sensor-specific thermal calibration constants.

Land surface emissivity (E) was estimated from NDVI via the proportion of vegetation (PV):

$$PV = [(NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min})]^2$$

$$E = 0.004 \cdot PV + 0.986$$

Finally, emissivity-corrected LST was computed as:

$$LST = BT / [1 + (\lambda \cdot BT / \rho) \cdot \ln(E)]$$

where λ is the wavelength of emitted radiance and $\rho = h \cdot c / \sigma$ ($1.438 \times 10^{-2}\ m\ K$); the equivalent working form used in ArcGIS raster algebra was $LST = BT + W \cdot (BT/14380) \cdot \ln(E)$, with W the wavelength constant for the relevant thermal band.

3.4 NDVI

NDVI was computed from the red and near-infrared surface reflectance bands (Band 4 and Band 5 for OLI; equivalent bands for TM/ETM+) as :

$$NDVI = (NIR - Red) / (NIR + Red)$$

NDVI ranges from -1 to $+1$; values above roughly 0.3 indicate dense, healthy vegetation, values near zero indicate sparse or non-vegetated surfaces, and negative values typically correspond to open water (Dymond et al., 1992; Small & Wu, 2006).

3.5 Land use/land cover (LULC) Classification

Land use/land cover (LULC) maps were produced using ArcGIS 10.8's supervised Maximum Likelihood Classification (MLC) (Anderson, 1976), algorithm for the years 2000, 2010, and 2020. The study area was classified into six broad LULC classifications—Water Body, Open/Barren Land, Agriculture, Sand, Dense Forest, and Settlement—based on their spectral properties. To achieve accurate class representation, representative training samples for each land cover class were chosen and digitized from false-colour composite (FCC) images, using high-resolution Google Earth Pro imagery. The Maximum Likelihood Classification technique was then applied to assign each image pixel to the most probable land cover class by considering the spectral signatures of the training samples. The categorization accuracy was assessed using independently selected reference points and an error matrix. The reliability of the classified maps was evaluated by calculating the Producer's Accuracy (PA), User's Accuracy (UA), Overall Accuracy (OA), and Kappa Coefficient (K). The categorization results were deemed adequate because the overall accuracy exceeded Anderson's recommended minimum of 85%. In order to quantify class-to-class land use transitions and evaluate the spatiotemporal LULC dynamics between 2000 and 2020, post-classification comparison was carried out to create a change detection matrix.

3.6 Statistical analysis

Pixel-based statistical analysis was used to assess the association between land surface temperature (LST) and vegetation dynamics in each research year (2000, 2010, and 2020) throughout both the pre- and post-monsoon seasons. The LST and NDVI raster datasets were spatially integrated, and pixel values were extracted to investigate the link between surface temperature and vegetation cover. The Pearson correlation coefficient (r) was computed to ascertain the intensity and direction of the association between the two variables, and linear regression analysis was used to characterize the nature of the LST–NDVI relationship. The statistical analysis provided a quantitative assessment of plant density's influence on land surface temperature, as well as a comparison of seasonal and temporal fluctuations in the LST-NDVI connection across the study period.

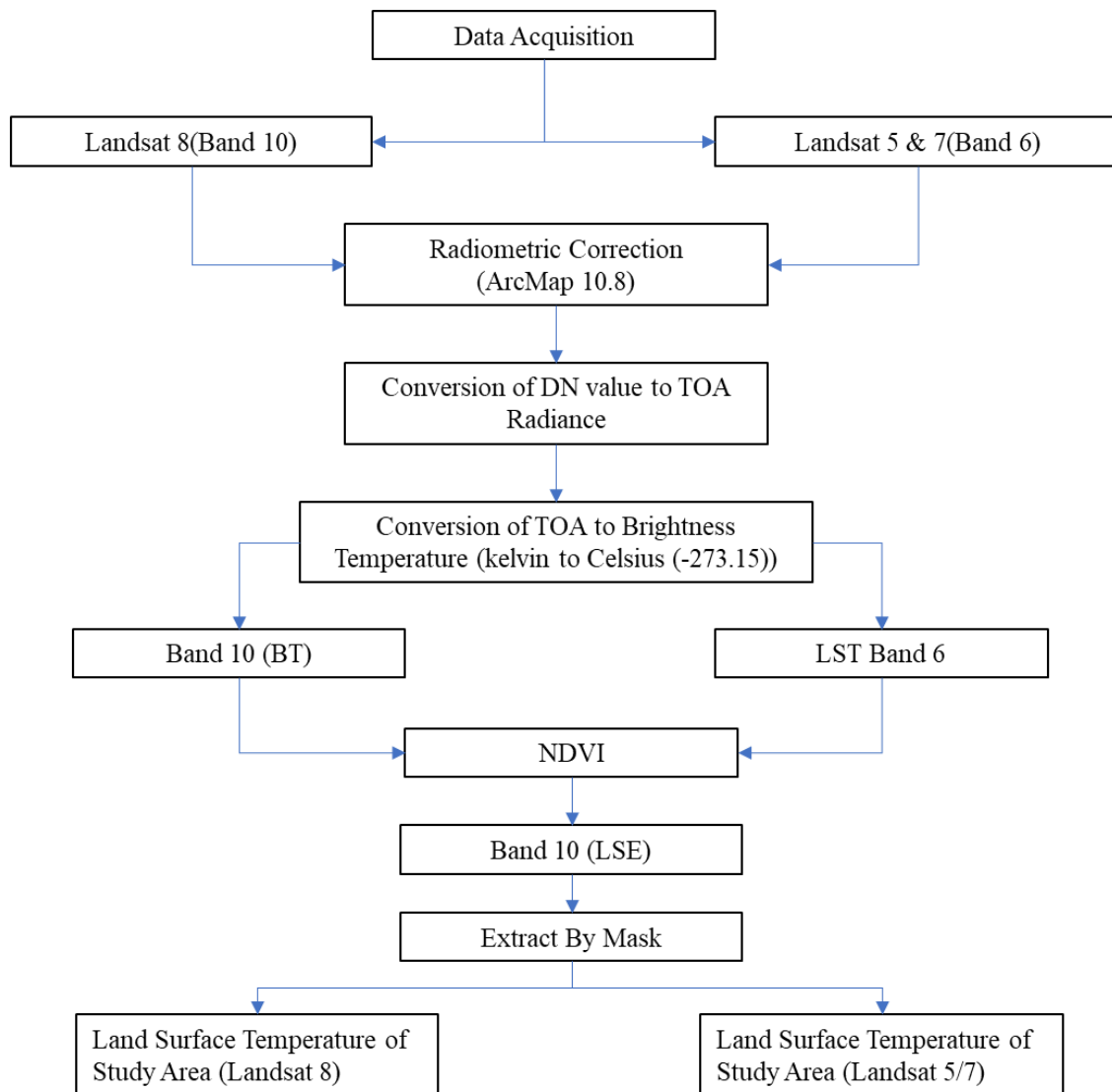


Figure 2 Flow of Data Processing

4. Results and Discussion

4.1 LULC classification and change (2000–2020)

The supervised classification maps and false-colored composites (Figure 3) represent a landscape mapped out around the Brahmaputra River channel, with dense forests concentrated in the southern area, which includes Boko, Chhaygaon, and Palasbari, and agricultural land predominantly occupying the northern section of the district, including Rangia, Koya, Kamalpur, and North Guwahati. The contiguous Meghalaya Plateau's ecological and geomorphological influence can be seen in this spatial pattern. Over the 2000-2020 period, the most noticeable land-use transition was the expansion of settlements along the Brahmaputra corridor, particularly in the Nagarbera, Goroimari, and Hajo areas, which was accompanied by a very moderate but consistent rise in open and barren terrain.

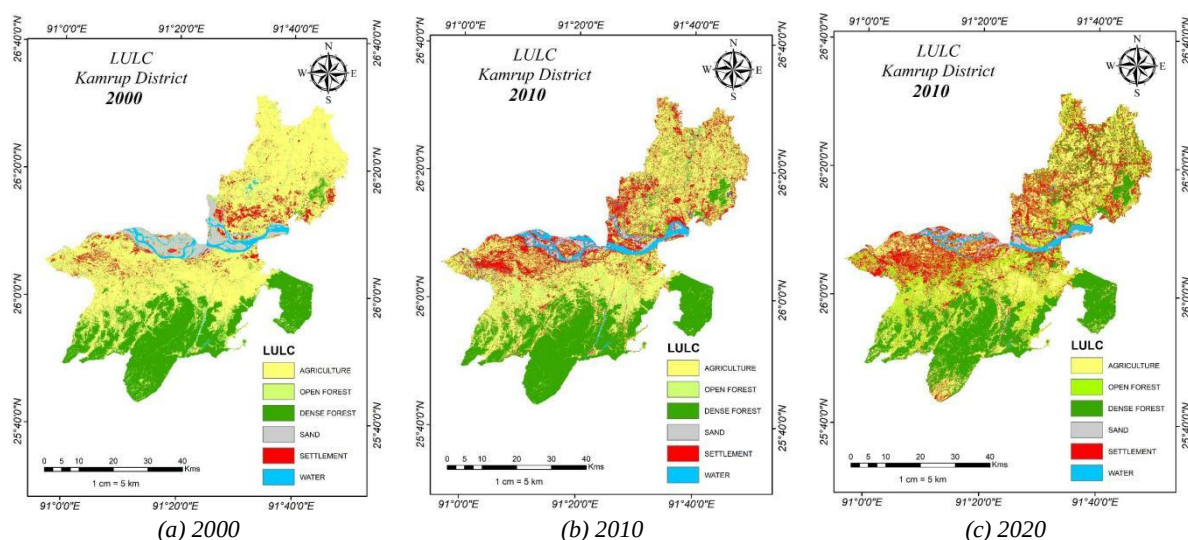


Figure 3 Supervised LULC classification of Kamrup district for 2000, 2010, and 2020

Overall accuracies of 91.1% (2000), 90.4% (2010), and 93.6% (2020) were achieved, with corresponding Kappa coefficients of 0.90, 0.88, and 0.92 (Table 2). The 85% standard that is typically used for dependable LULC categorization was exceeded by all overall accuracy values (Anderson, 1976). Water bodies and communities had 100% producer accuracy across all reference years. In comparison, the open forest class had the most uncertainty with surrounding land-cover categories, but maintained a consistent producer accuracy of 81.8% throughout the study period.

Table 2 ducer's accuracy (PA) and user's accuracy (UA, %) by LULC class, with overall accuracy and Kappa coefficient, 2000–2020.

LULC Class	2000 PA	2000 UA	2010 PA	2010 UA	2020 PA	2020 UA
Open Forest	81.82	80.00	81.82	90.00	81.82	90.10
Water Body	100.00	88.23	100.00	90.00	100.00	91.49
Sand	90.91	100.00	83.33	100.00	90.91	100.00
Settlement	100.00	90.00	100.00	80.00	100.00	90.00
Dense Forest	90.91	88.61	100.00	92.50	100.00	100.00
Agriculture	100.00	100.00	81.82	90.00	90.00	90.00
Overall Accuracy (%)	91.14		90.42		93.60	
Kappa Coefficient	0.90		0.88		0.92	

The observed LULC dynamics are statistically supported by the class-to-class transition matrix (Table 3). The agricultural land in the district declined from 1,421 km² (45.8%) in 2000 to 1,071 km² (34.5%) in 2020. Agricultural land (324.9 km²) and barren land (282.0 km²) were the most common identified conversion pathways. The settlement area increased from 182.7 km² to 728.9 km², whereas water bodies decreased from 82.9 km² to 73.1 km², partially due to conversion into sand. The area of dense

forest decreased from 821.6 km² to 687.3 km² during the transition period, with no recorded conversion to agricultural land. The preponderance of deep woodland in the district's comparatively difficult southern region is consistent with this pattern.

Table 3 LULC class transition matrix, Kamrup district, 2000–2020 (area in km²).

From \ To (2000→2020, km ²)	Agriculture	Dense Forest	Open Forest	Sand	Settlement	Waterbody	Total 2000
Agriculture	805.4	0.0	282.0	2.0	324.9	6.6	1420.7
Dense Forest	108.7	687.3	6.3	0.0	19.4	0.0	821.6
Open Forest	156.9	0.0	146.7	25.6	176.6	0.0	505.9
Sand	0.0	0.0	0.0	58.7	0.0	29.3	88.0
Settlement	0.0	0.0	0.0	0.0	182.7	0.0	182.7
Waterbody	0.0	0.0	0.0	20.2	25.4	37.2	82.9
Total 2020	1071.0	687.3	435.0	106.4	728.9	73.1	3101.8

4.2 Spatio-temporal distribution of LST

Between 2000 and 2020, land surface temperature (LST) increased across the district, with a much faster rate of warming during the pre-monsoon season than during the post-monsoon season (Figures 4 and 5; Table 4). The maximum pre-monsoon LST climbed from 27.1 °C in 2000 to 34.1 °C in 2010, and then to 38.7 °C in 2020. The minimum pre-monsoon LST, on the other hand, showed a more gradual rise, going from 14.7 °C to 19.7 °C before marginally dropping to 18.2 °C in 2020. The exposed sandbars, the Brahmaputra River's channel margins, and the built-up corridor north of the river, especially around Hajo, consistently had the highest LST values during all three pre-monsoon observations, while the dense forest tracts consistently had the lowest temperatures.

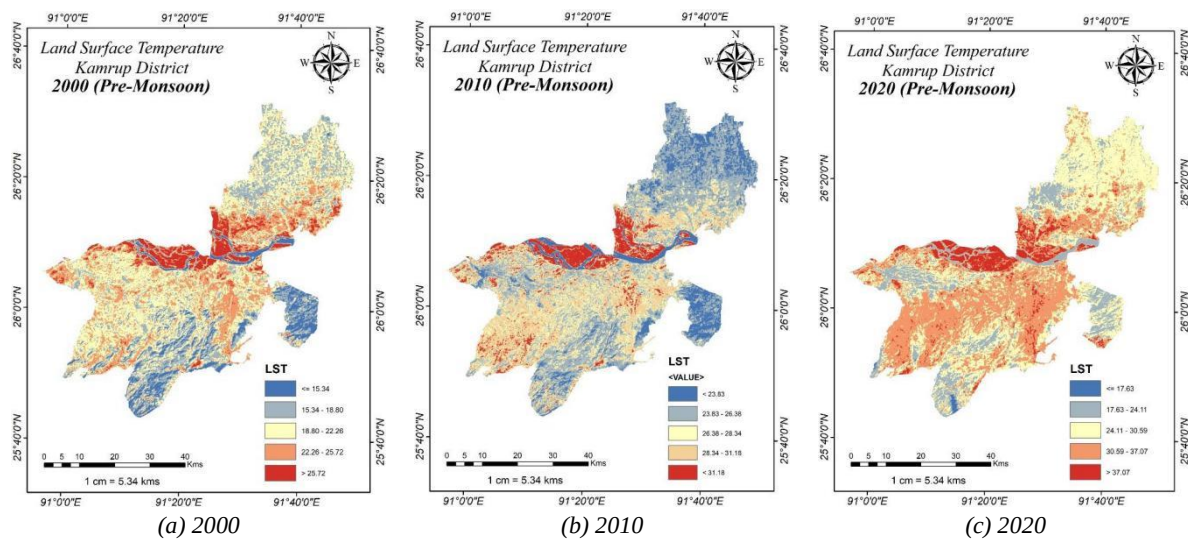


Figure 4 Spatial distribution of pre-monsoon LST, Kamrup district, 2000–2020

Post-monsoon LST exhibited a similar warming trend but with substantially lower magnitude than during the pre-monsoon season. Maximum post-monsoon LST remained unchanged at 24.8 °C in both 2000 and 2010 before increasing to 27.5 °C in 2020, whereas minimum LST increased progressively from 11.6 °C to 15.8 °C and 16.4 °C over the corresponding years (Table 4). The comparatively weaker post-monsoon warming is consistent with enhanced evaporative cooling and higher soil moisture availability following the monsoon, which attenuate the influence of land-cover change on surface thermal conditions relative to the drier, radiation-dominated pre-monsoon season.

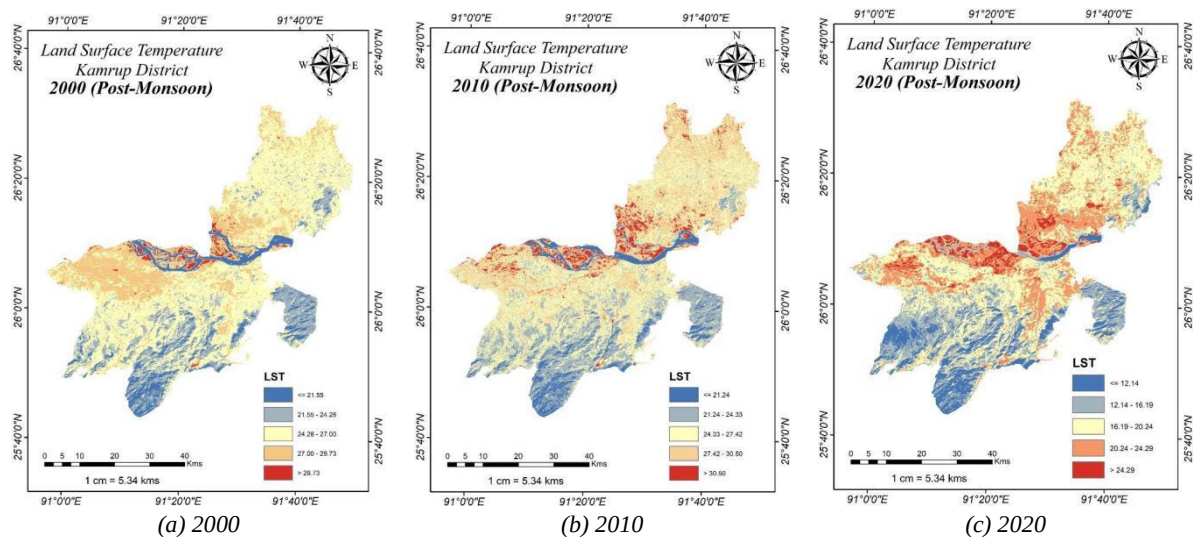


Figure 5 Spatial distribution of post-monsoon LST, Kamrup district, 2000–2020.

4.3 Spatio-temporal distribution of NDVI

Over the course of the investigation, NDVI values varied from -0.38 to 0.70 (Table 4). Water basins, sand deposits, and populated areas were consistently linked to the lowest values, whereas dense forests and agricultural land had the greatest values. The mean post-monsoon NDVI decreased from 0.40 in 2000 to 0.33 in 2010 and then to 0.27 in 2020, indicating a gradual decrease in the district's overall vegetation greenness and canopy density, even if the minimum and maximum NDVI extremes showed minimal interannual fluctuation. This pattern is in keeping with the LULC analysis, which shows that rather than a constant drop in vegetation condition within the same land-cover categories, vegetated surfaces were more converted into open or built-up land uses.

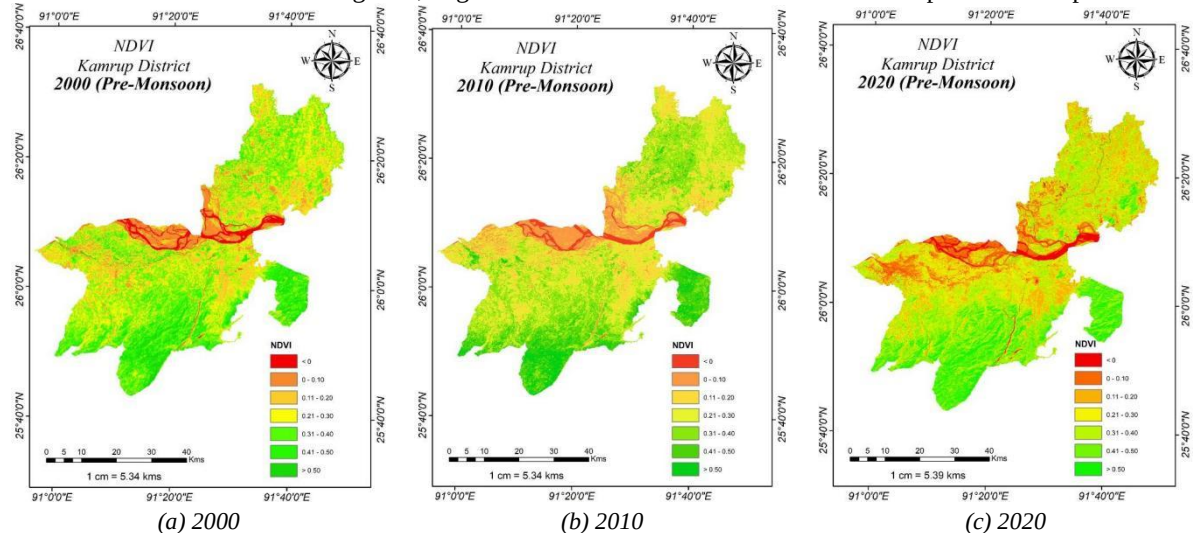


Figure 6 Spatial distribution of pre-monsoon NDVI, Kamrup district, 2000–2020.

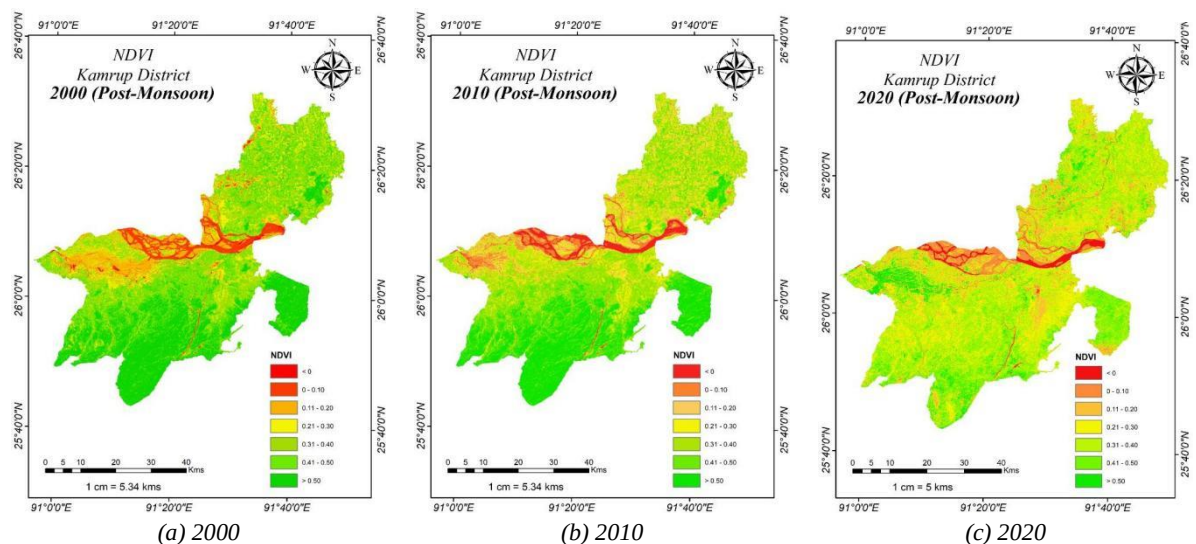


Figure 7 Spatial distribution of post-monsoon NDVI, Kamrup district, 2000–2020

4.4 LST–NDVI correlation

LST and NDVI showed a constant negative correlation across all years and seasons, confirming vegetation's well-known cooling effect on land surface temperature (Table 4). Correlation coefficients were -0.52 (2000), -0.48 (2010), and -0.59 (2020) during the pre-monsoon season, while the corresponding post-monsoon values were marginally higher at -0.62 , -0.68 , and -0.57 , respectively. Greater differences in vegetation canopy and soil moisture between vegetated and non-vegetated areas after the monsoon, when vegetation is completely grown and moisture availability is quite high, are consistent with the stronger post-monsoon association. This seasonal trend is consistent with findings from other tropical and subtropical regions (Yuan & Bauer, 2007; Ibrahim, 2017). The interpretation that the observed increase in LST in Kamrup is linked to the gradual loss of agricultural and forest cover indicated in Section 4.1 rather than being an artifact of a single anomalous satellite scene is further supported by the consistent moderate-to-strong negative correlations across all six year–season combinations.

Table 4 LST and NDVI minima/maxima and LST–NDVI correlation coefficient, by season and year

Season	Year	LST min (°C)	LST max (°C)	NDVI min	NDVI max	Correlation (r)
Pre-monsoon	2000	14.71	27.10	-0.33	0.52	-0.52
Pre-monsoon	2010	19.74	34.08	-0.09	0.49	-0.48
Pre-monsoon	2020	18.23	38.72	-0.05	0.42	-0.59
Post-monsoon	2000	11.64	24.77	-0.38	0.70	-0.62
Post-monsoon	2010	15.78	24.82	-0.42	0.67	-0.68
Post-monsoon	2020	16.36	27.50	-0.13	0.49	-0.57

5. Conclusion

This study examined changes in vegetation cover, land surface temperature (LST), and land use/land cover (LULC) in Kamrup district, Assam, using a 21-year, six-Spatio-temporal Landsat time series. Between 2000 and 2020, the Brahmaputra corridor had a significant conversion of agricultural and open-forest area to settlements and barren ground, according to the LULC categorization, which had overall accuracies ranging from 90% to 94%. The maximum pre-monsoon LST rose by about 11.6°C throughout that time, significantly more than the comparable post-monsoon increase. The moderating effect of vegetation on surface temperature conditions was demonstrated by the persistent moderate-to-strong negative correlation ($r = -0.48$ to -0.68) between LST and NDVI throughout all years and seasons. When taken as a whole, these results show that the floodplain landscape has experienced measurable surface warming due to the progressive loss of vegetative cover brought on by settlement development, with the biggest effects happening during the comparatively dry pre-monsoon season.

6. LIMITATIONS AND SCOPE FOR FUTURE WORK

1. Temporal sampling: the analysis rests on three reference years (2000, 2010, 2020) with a single pre-monsoon and post-monsoon scene each. This is sufficient to show change between three points in time but does not constitute a statistically fitted long-term trend, and single-date scenes are sensitive to the specific weather conditions on the day of acquisition.
2. Cross-sensor comparison: LST was retrieved from three different sensors (TM, ETM+, OLI/TIRS) with differing spectral, spatial, and thermal-band characteristics. Although a consistent retrieval algorithm was applied, small inter-sensor calibration differences were not separately quantified and could contribute to part of the observed change.
3. No ground validation of LST: retrieved LST values were not cross-checked against in-situ station or near-surface air-temperature records, so the absolute accuracy of the retrieval (as opposed to its internal, relative consistency with NDVI and LULC) is not independently established.

4. Confounding drivers not isolated: the negative LST–NDVI relationship is documented, but other known controls on LST — impervious surface fraction, soil moisture, local meteorology, and elevation — were not modelled separately, so the vegetation effect is not statistically isolated from these covariates.
5. Attribution: the study identifies an association between vegetation loss and LST rise but does not establish a causal mechanism separating land cover change from broader regional warming or from atmospheric conditions specific to the acquisition dates.
6. Geographic scope: findings are specific to Kamrup district's floodplain and agriculture–forest mosaic and should not be extrapolated to other districts of Assam without independent analysis.

Future work could extend the time series to annual or sub-annual frequency using the full Landsat and Sentinel-2/3 archives, incorporate ground-based temperature validation, and statistically control for impervious surface fraction and soil moisture.

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The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression, "One of us (R.B.G.) thanks..." Instead, try "R.B.G. thanks". Put applicable sponsor acknowledgments here; DONOT place them on the first page of your paper or as a footnote.

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