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Research Article

Investigating Spatiotemporal Patterns of Land Surface Temperature in Relation to Urbanization and Salinity in a Coastal District of Bangladesh

Md. Osman Gani Rasel[1], Md. Mahabub Rahman*,[2], Md. Mahfuj Ahmed Sizan[3]

[1,2,3]*Department of Civil Engineering, Hajee Mohammad Danesh Science and Technology University, Dinajpur-5200, Bangladesh*

Keywords

LST, MODIS data, Salinity effects, Spatiotemporal analysis, Khulna district.

Abstract

The current study aimed to quantifying the spatiotemporal variation of land surface temperature (LST) and investigate its association with vegetation greenness, built-up areas, and salinity in Khulna District of Bangladesh between 2002 and 2020 by processing MODIS derived products in Google Earth Engine (GEE) platform. The Mann–Kendall (MK) test and Sen's slope estimator were used to quantify temporal trends while the Pearson correlation analysis was employed to examine relationships among the variables. Results did not show any long term statistically significant monotonic trend at the district scale of the LST (τ= 0.0435, p=0.3304) with an estimated trend of 0.002°C/yr. The monthly mean LST values varied between 20.9°C and 32.3°C and were higher in peri-urban and urban areas in general. The normalized difference vegetation index (NDVI) had a significant positive trend (0.0002 yr^{-1}, with τ=0.1365, p=0.0023), but had a very weak and non-significant relationship with LST (r=0.0455, p=0.4964). The normalized difference built-up index (NDBI) showed a slight decreasing trend (−0.0002 yr^{-1}; τ=−0.1276, p=0.0043), whereas LST was weakly positively correlated with built-up intensity (r=0.16, p=0.016), probably due to spectral mixing and surface reflectance properties rather than actual decreases in urbanization. No significant temporal trend was observed in the spectrally derived salinity proxy but there was a weak positive correlation with LST (r=0.18, p=0.0054) especially near coastlines. However, all these statistically significant relations explained less than 4% of the LST variance (R^2 < 0.04) and suggested that other climatic and environmental factors have the main influence on the variability in LST.

1. Introduction

Land surface temperature (LST) is one of the key biophysical parameters which represents the interaction between the land surface and the atmospheric processes and has thus emerged as one of the fundamental parameters for monitoring environmental change, climate variability and anthropogenic activities. With rapid urbanization, especially in vulnerable coastal area, the dynamic land use/land cover (LULC) change and vulnerability to climate induced stress have led to an increase research attention in LST in the recent years [1–4]. The spatial and temporal patterns of LST changes are mostly controlled by the surface energy balance related to land-cover properties, vegetation growth, moisture, and albedo and emissivity characteristics [5–7]. Urbanization, by lowering the amount of natural vegetation and increasing the number of impervious surfaces, has a significant effect on LST variability, as it changes hydrological capacity and thermal properties [2, 8]. Impervious surfaces in urban infrastructure have a tendency to absorb and retain heat, causing localized warming effects called Urban Heat Islands (UHIs) that increase thermal discomfort to ecosystems and humans [9–10]. However, vegetation buffers the effects of increasing evapotranspiration and shading, which lowers surface temperatures [5, 11]. However, several recent studies have shown that the cooling effect of vegetation can also differ depending on location and is very context-sensitive regarding the living surrounding land-use structures and vegetation density [3–4]. Spectral salinity index is another relatively less studied parameter that affects the LST in coastal zone. Salinity-induced changes in soil moisture, surface reflectance (albedo) and thermal conductivity influence land surface thermal behavior [11-13]. These surface moisture contents also influence the vegetation cover and spectral properties [1, 3] and indirectly LST. But the effect of the interaction between salinity and urbanization on LST is poorly understood particularly in deltaic and coastal regions.

Bangladesh is one of the most climate change-vulnerable countries in the world, and rapid urbanization, sea level rise and salinity intrusion [12–13] are a great risk. The low-lying topography and the geographic location of the coastal region of Khulna District in the southwest of Bangladesh, where the Sundarbans mangrove ecosystem is located and anthropogenic activities are rapidly increasing, are significant hotspots in which these processes converge and are especially susceptible to environmental and thermal stress [9, 11]. Although several studies have focused on the impacts of the urban heat island in Bangladesh or on the difference in LST and LULC, few have tried to understand the integrated and interactive pattern of vegetation, built-up area, and salinity with the long-term variation and change rate of LST as spatiotemporal metrics. With the development of satellite remote sensing technologies and cloud-based geospatial platforms, the ability to observe dynamic changes in the environment at large space and time scales has significantly improved. The MODIS products provide long-term datasets of LST, VIs, and surface properties that are consistent in space and time [14, 15]. Likewise, GEE makes it possible to perform rapid processing of large geospatial data and provides powerful spatiotemporal analysis. Non-parametric statistical techniques like MK test and Sen's slope estimator have been more commonly employed to identify trends in environmental variables as they do not need normally-distributed data [16–17]. Correlation analysis methods are widely used for the quantitative analysis of the relationship between LST and its related factors (such as vegetation indices (NDVI), built-up indices (NDBI) and environmental indicators) at a large scale [18]. However, there is still a significant lack of understanding of the interactions among multiple environmental drivers in space and time in shaping LST in coastal systems, particularly at larger temporal

*Corresponding Author: mmr.civil@hstu.ac.bd
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scales. The studies currently available focus either on urbanization or on vegetation and have not paid sufficient attention to salinity [19]. This gap needs to be filled to build climate-smart urban and coastal management options.

Therefore, the present study is aimed to analyze the spatiotemporal dynamics of LST in Khulna District of Bangladesh in the period 2002-2020 and its association with vegetation greenness, built-up intensity and spectral salinity index using multi-temporal MODIS data in the Google Earth Engine platform. This study uses a combination of remote sensing analysis and statistical trend and correlation analysis and is thus capable of providing place-specific understanding of the major relationships between the environmental factors and the surface thermal variations of sensitive coastal environments. This will help improve the monitoring of coastal ecosystems and give informative data on sustainable land-use planning.

2. Methodology

2.1. Study area

This study was conducted in Khulna District, located in the south-western coastal zone of Bangladesh, approximately between 21°30′–23°00′ N latitude and 88°30′–89°45′ E longitude (Figure 1). The environmental sensitivity of the district results from rapid urbanization, vegetation change, and soil salinization, which are determined by coastal and hydro-climatic factors. Dominated by low-lying topography and bordering the Sundarbans mangrove region, Khulna therefore represents an appropriate study area for examining long-term interactions between LST variations, vegetation phenology, built-up expansion, and salinity status.

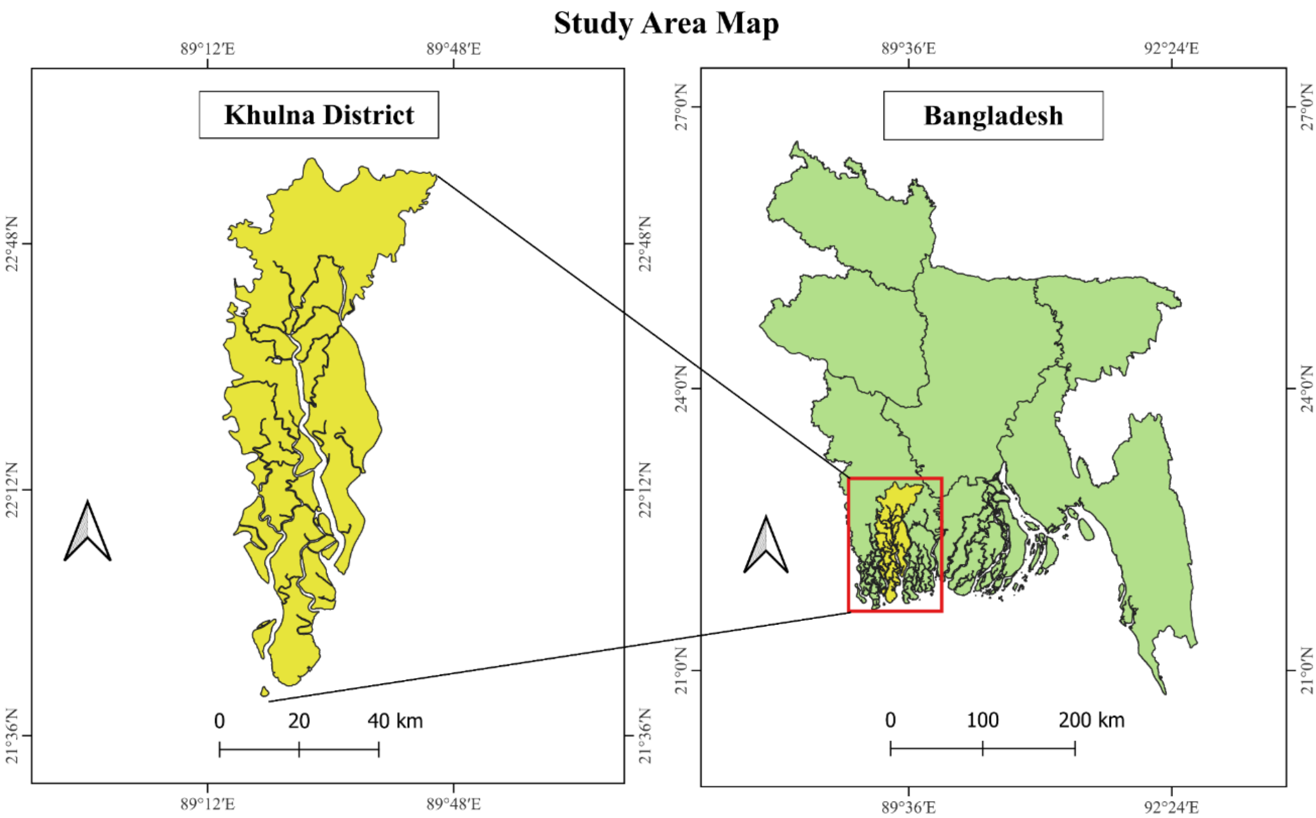


Figure 1. Map of Khulna District, Bangladesh

2.2. Data sources, preprocessing and workflow description

Multi-temporal MODIS satellite data were used for exploring spatiotemporal environmental changes across Khulna District. The datasets used, the derived variables, and the spatial and temporal resolutions are described in Table 1. LST was retrieved from the MOD11A2 (Version 6.1) product (8-day composites, 1 km resolution). Vegetation status was characterized using MOD13A2 NDVI (16-day composite, 1 km resolution), and built-up and salinity data were obtained from the MOD09A1 surface reflectance product at a spatial resolution of 500 m [20–21].

Table 1. MODIS datasets and derived variables used in the study

Dataset	Product Version	Variable Derived	Spatial Resolution	Temporal Resolution	Time Coverage
MOD11A2	Version 6.1	LST	1 km	8-day composite	2000–2020
MOD13A2	Version 6.1	NDVI	1 km	16-day composite	2000–2020
MOD09A1	Version 6.1	Surface Reflectance (NIR, SWIR, Green bands)	500 m	8-day composite	2000–2020

All data was analyzed in the GEE cloud-based computing platform. Cloud contamination and retrieval errors were minimized through pixel-wise quality control procedures. For LST, the QC_Day bitmask was applied to keep only pixels with valid quality indicators and the pixel values were converted from Kelvin to degrees Celsius following the conversion formula (Equation 1).

$$LST\ (°C) = LST\ (K) - 273.15 \tag{1}$$

NDVI data were filtered using the SummaryQA band to only high-quality observations, and rescaled to standard NDVI units. The StateQA band was used for selecting cloud-free surface reflectance pixels for NDBI and salinity derivation [11]. Monthly mean layers were generated for each of the variables and cropped to the boundary of Khulna District. Figure 2 provides an overview of the general methodological approach. The workflow starts with the multi-temporal MODIS data retrieval in GEE, quality controlling data, then processing and computation of LST, NDVI, NDBI and salinity indices [6, 8]. Processed output raster's are then standardized in GIS and analyzed statistically in python to detect temporal trends and relationships between variables.

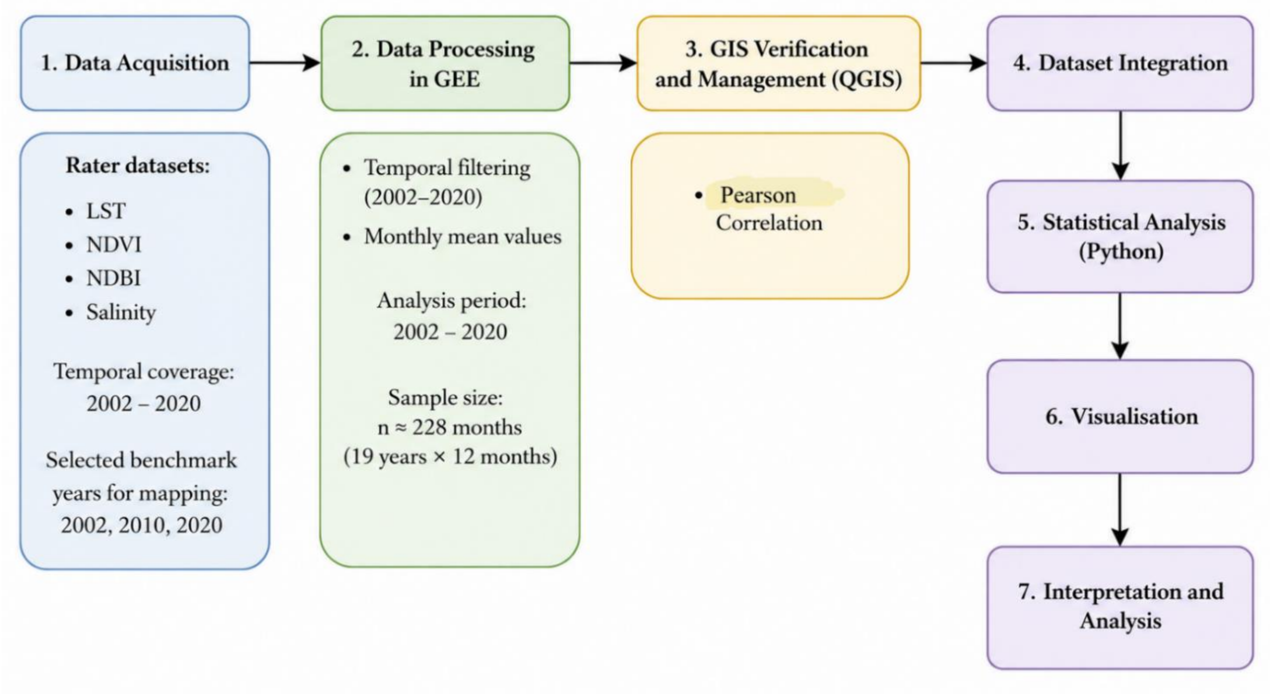


Figure 2. Workflow diagram illustrating the data processing and analytical framework

2.3. Evaluation of environmental indicators and spatial mapping process

Environmental indicators were calculated using well established remote sensing formulations to quantify vegetation greenness, built up intensity and salinity indicator conditions. The NDVI (Equation 2), was used to represent greenness of vegetation:

$$NDVI = \frac{NIR-Red}{NIR+Red} \tag{2}$$

In which NIR and Red are the near-infrared and red reflectance bands, respectively. The NDBI, which is based on two reflectance bands (near-infrared and shortwave infrared reflectance, Equation 3), was used to quantify built-up intensity.

$$NDBI = \frac{SWIR-NIR}{SWIR+NIR} \tag{3}$$

A spectral salinity index based on the green and shortwave infrared reflectance bands (Equation 4) was used to estimate spectral salinity proxy conditions:

$$SI = \frac{Green-SWIR}{Green+SWIR} \tag{4}$$

where Green and SWIR are the green and shortwave infrared reflectance bands, respectively. This formulation includes the spectral response of saline affected surfaces that show characteristic reflectance patterns in these bands.

All processed datasets have been heuristically minimized for error by being processed together in the Google Earth Engine (GEE) environment with the same spatial sampling and temporal aggregation [4]. To examine coherent multi-year long-term trends with the minimum short-term fluctuations and noises, monthly mean composites were produced for each variable. These adapted raster data layers were then exported to and spatially validated, reprojection and resampling takes place in using ArcGIS to ensure uniform spatial resolution on all levels. The ArcGIS platform, a widely used geographic information system (GIS), was used for mapping preparation and final spatial visualization that is effective in representing complex patterns of spatial forces [22] to a wide range of environmental and geoscientific, water resource related and infrastructure studies [23–28]. To ensure spatial consistency, the analysis was performed on all the datasets, reprojected into a shared spatial reference. Thematic maps were prepared based on suitable classes, schemes and legends as per graphological conventions so that the thematic maps are as clear and accurate as possible in them.

2.4. Trend evaluation of environmental indicators

Non-parametric MK test and Sen's slope estimator were used for the temporal trends of environmental variables. The MK test statistic (S) is the following: (Equation 5):

$$S = \sum_{i=1}^{m-1} \sum_{j=i+1}^{m} sgn(p_j - p_i) \tag{5}$$

where m is the number of observations, p_i and p_j are the data value at time step i and j (j > i), and sgn() is the sign function (Equation 6):

$$sgn(p_j - p_i) = \begin{cases} +1, & If\ p_j - p_i > 0 \\ 0, & If\ p_j - p_i = 0 \\ -1, & If\ p_j - p_i < 0 \end{cases} \tag{6}$$

The monotonic trend was calculated by using Equation 7.

$$Q = \text{median}\left(\frac{p_j - p_i}{j - i}\right), \quad j > i \tag{7}$$

Where Q is the slope estimator of the sen.

2.5. Seasonal analysis

The study period was subdivided in four seasons according to the monsoon calendar of Bangladesh: pre-monsoon (March to May), monsoon (June to September), post-monsoon (October to November) and winter (December to February) to study the seasonal variability. For each season, mean values were calculated for LST, NDVI, NDBI, and SI for the three study years (2002, 2010 and 2020). These layers were then exported in raster format to QGIS where spatial validation, reprojection and resampling were carried out to ensure a consistent spatial resolution for all layers. The spatial resolutions are different for the various datasets used in this study. Land surface temperature (LST) and normalized difference vegetation index (NDVI) products derived from MODIS data have a spatial resolution of 1 km, while indices based on surface reflectance such as normalized difference built-up index (NDBI) and spectral salinity index (SI) are originally available at 500 m resolution. Every variable was analyzed at the same spatial scale of 1 km to allow for consistency in the spatial analysis.

While reducing the 500 m datasets to regional level in Google Earth Engine, these datasets were presented in an effective 1 km resolution through mean-based spatial averaging. This aggregation method maintains the spatial representative attributes of the finer resolution data and does not over-enhance the spatial detail. No interpolation-based re-sampling method was used as this could generate artefacts or distort relationships between pixels, especially in coastal areas where the composition of the data is highly heterogeneous. Standard cartographic conventions were used to prepare the thematic maps, using appropriate classification schemes, color ramps and legends to ensure clarity and accuracy in spatial visualization.

2.6. Correlation assessment

Pearson's correlation coefficient (Equation 8) was used to investigate the relations between LST and other environmental variables.

$$\mathrm{r} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{8}$$

where x is a set of observations of LST and y is a set of observations of the environmental variable of interest.

District level monthly average data for 2002-2020 ($n \approx 228$: 19 years $\times$ 12 months) were used in the correlation analysis. While spatial patterns are shown for a small number of benchmark years (2002, 2010 and 2020), the entire time series was utilized to statistically capture inter-variable relationships.

2.7. Autocorrelation consideration

It is assumed that no serial autocorrelation exists in the data being used in the Mann–Kendall test; failure to do so could influence the significance of the trend. Because monthly mean values were utilized, the dataset is subject to seasonal serial autocorrelation. Failing to formally test for autocorrelation in this monthly time-series data severely limits the confidence of the trend analysis, representing a limitation of the current study. So, the widely used Mann–Kendall test was used. More advanced methods like trend-free pre-whitening or the modified Mann–Kendall test were not used but might be taken into account in future studies.

3. Results

3.1. Spatial variability of environmental variables

The spatial distribution maps (Figures 3–6) show the spatial distribution of LST, NDVI, NDBI, and spectral salinity proxy in the study area. LST ranges between about 20.9 °C and 32.3 °C, with high LST mainly located in the central urban and peri-urban areas and relatively low LST in vegetated and water-covered areas located in the south of the district (Figure 3). The vegetation cover on the NDVI distribution shows moderate to dense vegetation cover of 0.30 to 0.67 on the study area. The NDVI values are high in the southern and south-western portions of the study area which show the agricultural land and vegetation cover, while low values are seen in urban built-up areas (Figure 4). NDBI (Figure 5) represents built-up density with a range of -0.37 to -0.12 and higher values mostly found in urban cores and development corridors. High values are linked to high infrastructure density and impervious surfaces, low values to non-urban and vegetated areas. Salinity indicator values vary between -0.30 and 0.07 with higher salinity mostly occurring in the coastal and the extreme south of the district. Salinity is lower along the inland regions, where the influence of the coast is less. The maps as a whole show distinct differences in environmental conditions between urban, vegetated and coastal parts of the district.

3.2. Temporal trends of environmental variables

The results of the MK test and Sen's slope analysis are summarized in Table 2, while the graphical representation of the temporal variations is presented in Figures 7(a–d).

Table 2. MK test and Sen's slope analysis results

Variable	Trend	τ	Sen's slope	p-value	Significant (α=0.05)
LST_C	No trend	0.0435	0.0024	0.3304	No
NDVI	Increasing	0.1365	0.0002	0.0023	Yes
NDBI	Decreasing	-0.1276	-0.0002	0.0043	Yes
Salinity	No trend	0.0284	0.0000	0.5263	No

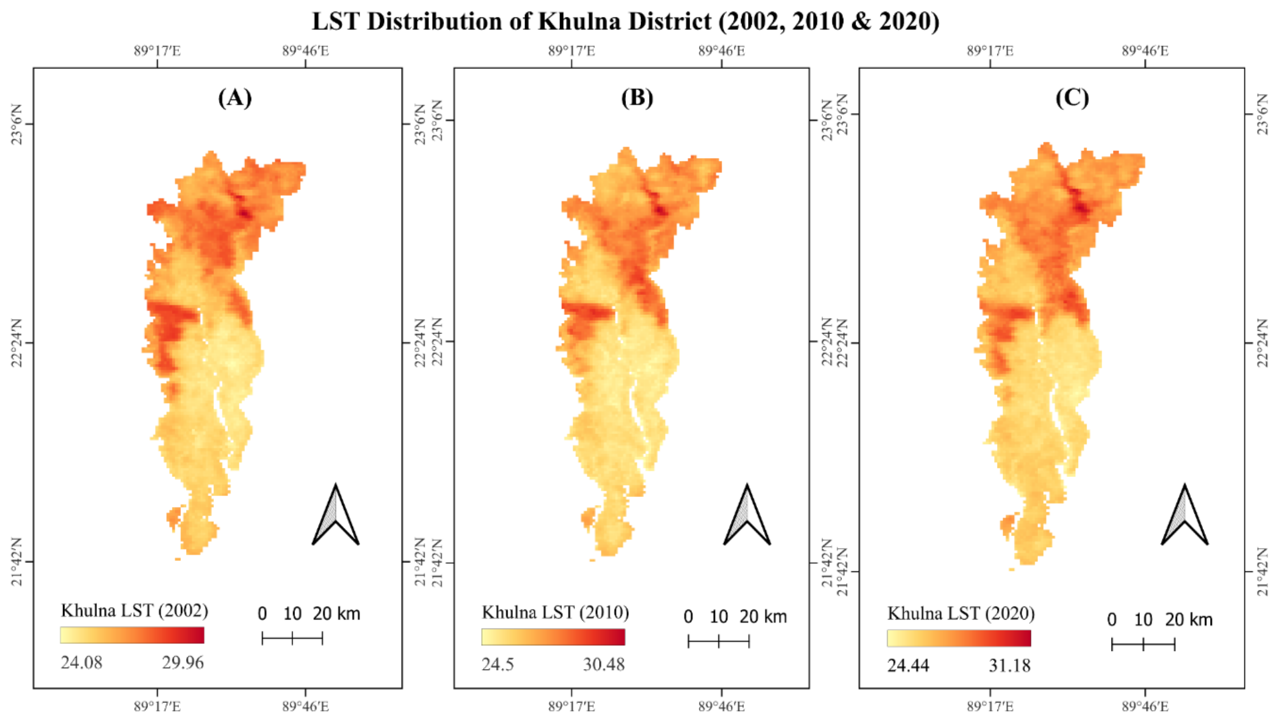


Figure 3. Spatial map of LST in Khulna District for (a) 2002, (b) 2010 and (c) 2020

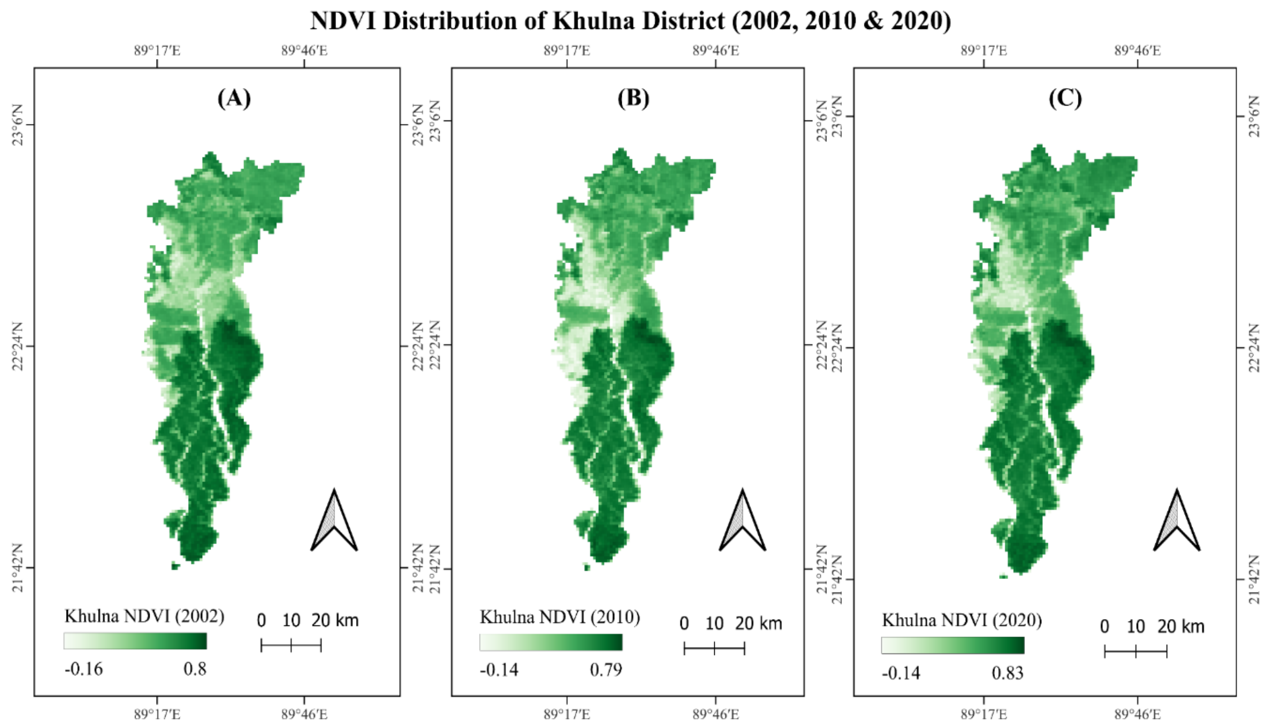


Figure 4. Spatial map of NDVI in Khulna District for (a) 2002, (b) 2010 and (c) 2020

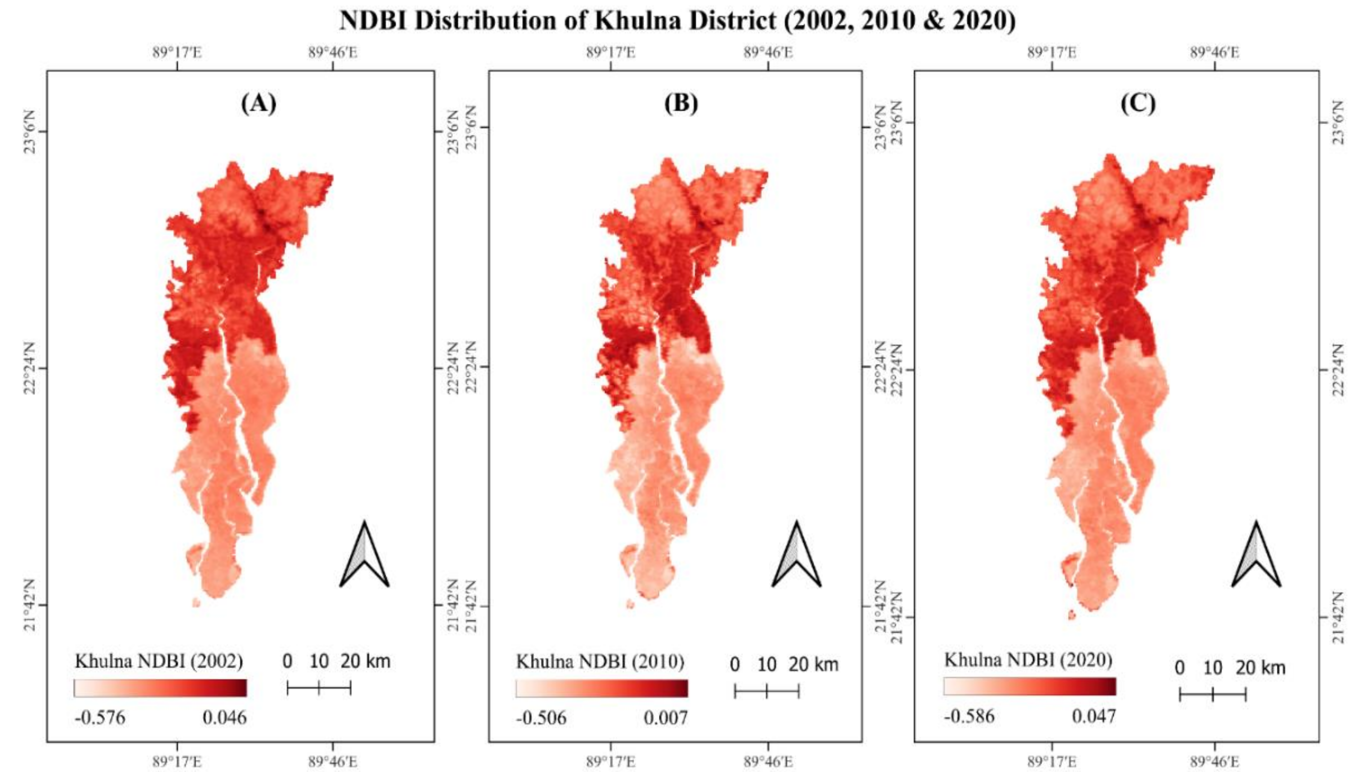


Figure 5. Spatial map of NDBI in Khulna District for (a) 2002, (b) 2010 and (c) 2020

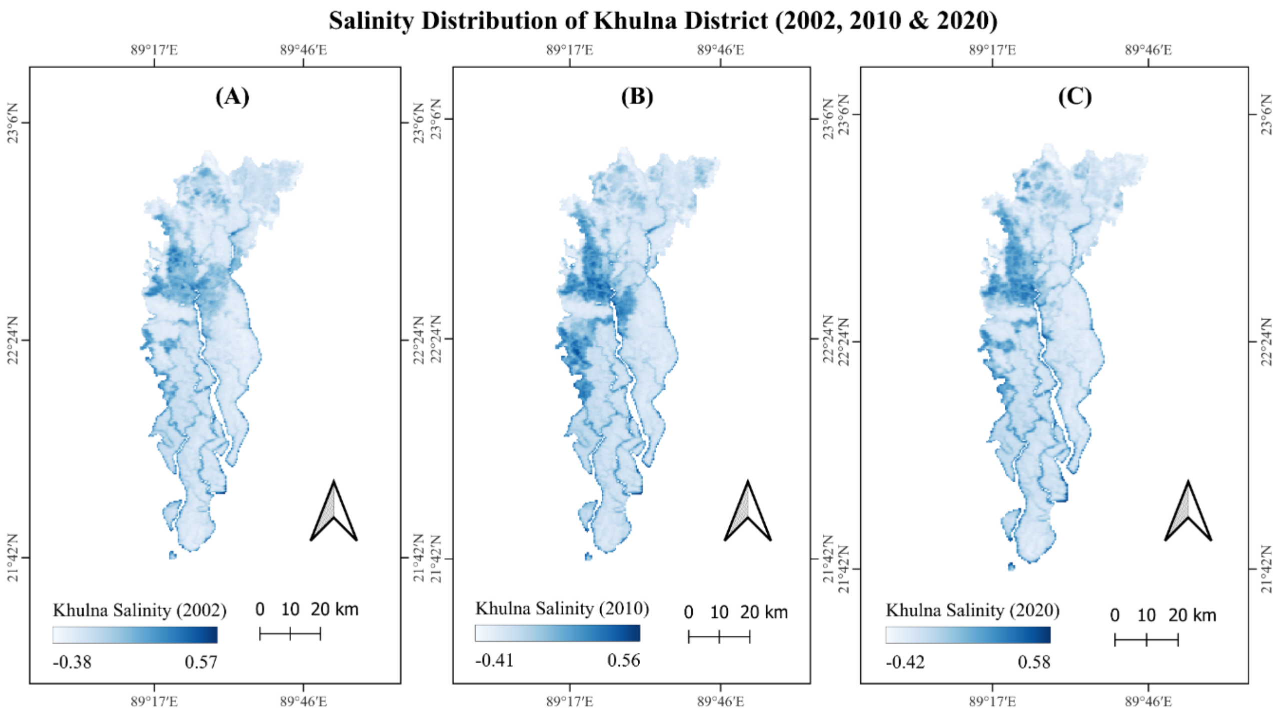
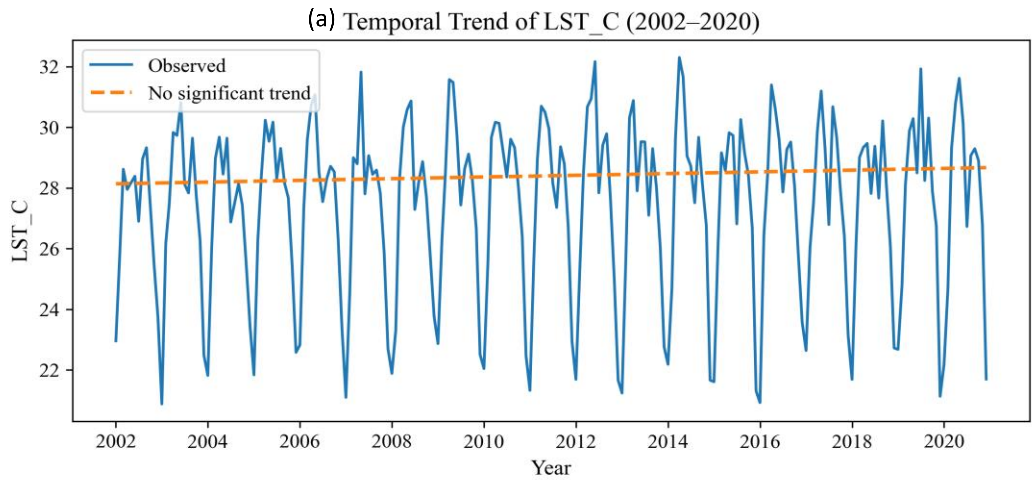


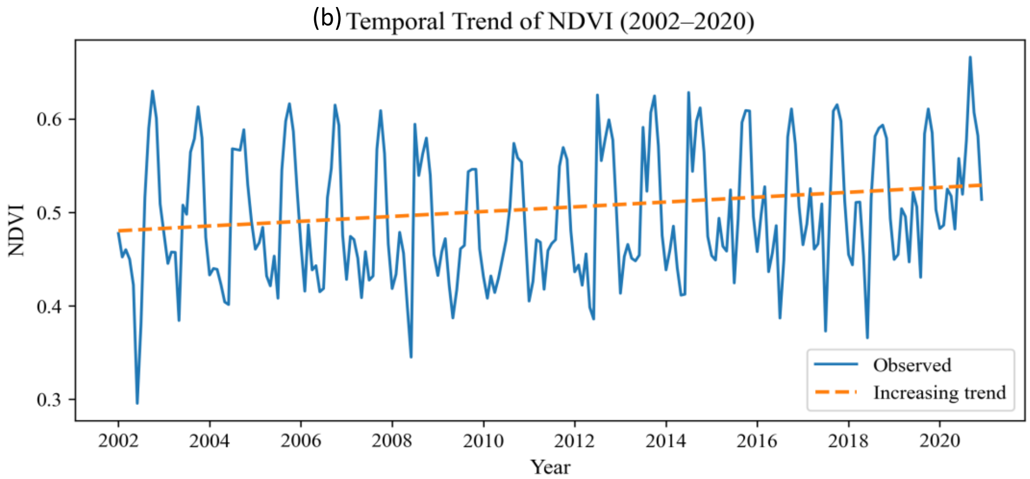
Figure 6. Spatial map of salinity in Khulna District for (a) 2002, (b) 2010 and (c) 2020

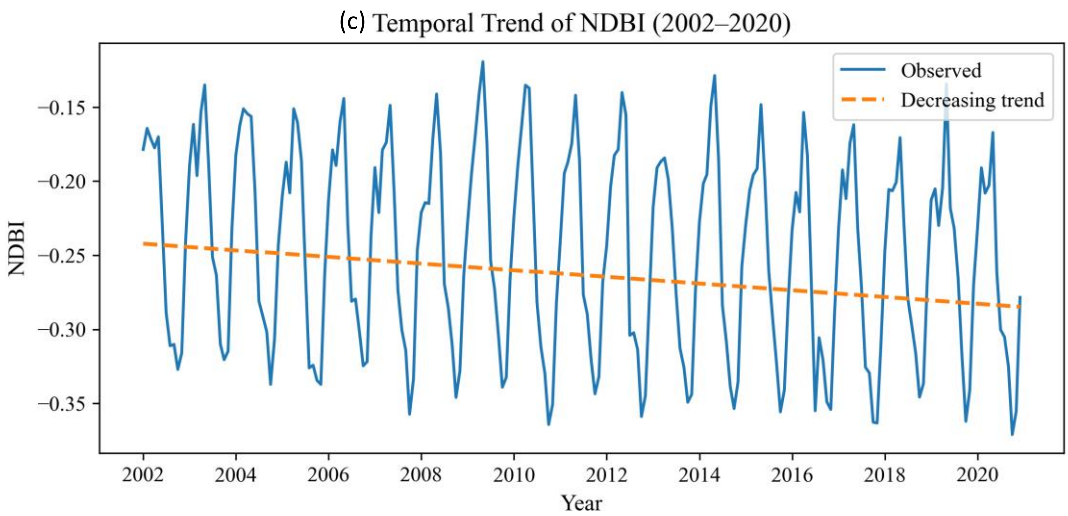
LST showed a weak positive trend (Figure 7a), with Kendall's $\tau = 0.0435$ and Sen's slope of 0.0024 °C yr^{-1}; however, the long-term warming signal was not statistically significant at the district level ($p = 0.3304$). In contrast, NDVI exhibited a significantly increasing tendency (Figure 7b), with Kendall's $\tau = 0.1365$ and Sen's slope of 0.0002 yr^{-1} ($p = 0.0023$), indicating a gradual improvement in vegetation greenness over the study period. NDBI also exhibited a statistically significant decreasing trend (Figure 7c), with $\tau = -0.1276$ and Sen's slope of −0.0002 yr^{-1} ($p = 0.0043$), suggesting that changes in surface reflectance properties may have occurred; however, this does not necessarily reflect an actual decrease in urban development and requires independent validation. Independent validation with the Global Human Settlement Layer (GHS-BUILT-S R2023A) however showed that the built-up surface area in Khulna district has shown a significant increase from 25.80 km^2 in 2000 to 45.23 km^2 in 2020, an increase of ~75.3% during the study period (in Table 3). This is because, despite the decrease in trend of NDBI, the actual decrease of the urban extent is not a true reflection, but is rather a result of 'spectral mixing effects' in which the progressive encroaching of built-up surfaces into vegetated and mixed land-cover areas suppressed the NDBI values at the 30 m Landsat pixel scale [29]. A monotonic trend in spectral salinity index was not statistically significant (Figure 7d) with τ = 0.0284 and p = 0.5263.

Table 3. Built-up area in Khulna district derived from GHSL data, for five epochs [30]

Year	Built-up Area (km^2)	Change from 2000 (km^2)	Change (%)
2000	25.8	—	—
2005	29.27	3.47	13.5
2010	33.83	8.03	31.1
2015	39.24	13.44	52.1
2020	45.23	19.43	75.3







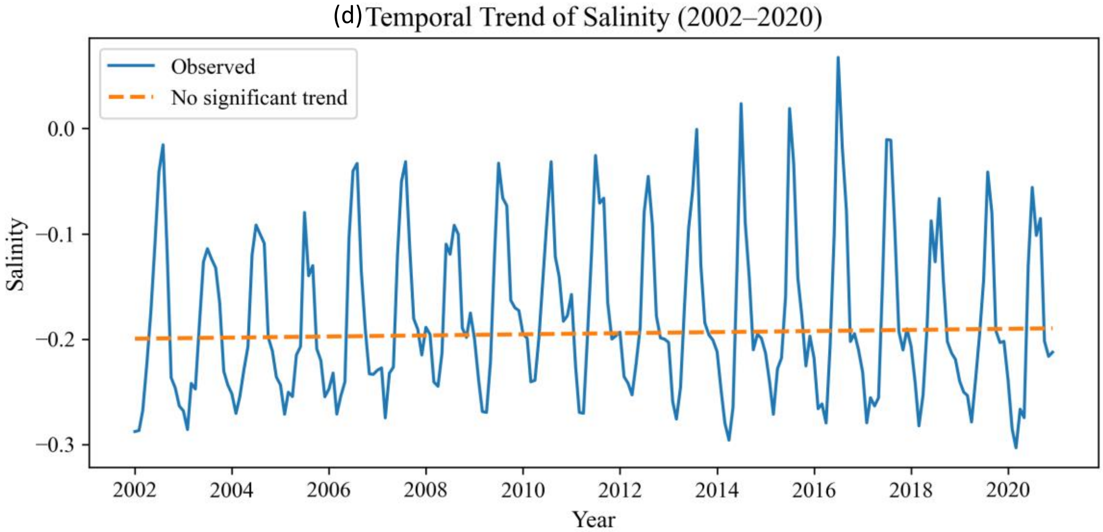


Figure 7. Temporal trends of (a) LST, (b) NDVI, (c) NDBI, and (d) salinity in Khulna District (2002–2020)

3.3. Correlation of LST with environmental parameters

The results of the correlation are presented in Table 4. Correlation between LST and NDVI is not significant with low value ($r = 0.0455$, $p = 0.4964$) and hence there is not much direct linear association between vegetation greenness and surface temperature at district level. The built-up intensity is weakly, but significantly, positively correlated with LST ($r = 0.1601$, $p = 0.0160$), which suggests a slightly warmer thermal condition around urban surfaces. The relationship between LST and spectral salinity index is also statistically significant ($r = 0.1845$, $p = 0.0054$), indicating that saline affected surfaces might be a contributing factor of higher land surface temperature especially in coastal areas.

Table 4. Pearson correlation coefficients of LST with other environmental variables

Variable	n	Pearson r	p-value	Significant (α=0.05)
NDVI	228	0.0455	0.4964	No
NDBI	228	0.1601	0.0160	Yes
Salinity	228	0.1845	0.0054	Yes

3.4. Seasonal variability

It was noticed that there is intra-annual variability in LST, NDVI, NDBI and spectral salinity index (SI) with Bangladesh's monsoon climate dynamics while performing seasonal analysis of the data for three study years (2002, 2010 and 2020) (Table 5; Figure 8). LST was always highest during the pre-monsoon season (28.3–30.2°C) and lowest during winter (22.8–23.9°C) owing to the strong seasonal thermal forcing of this coastal region, where the temperature regularly peaks during the pre-monsoon season due to dryness and intense solar radiation before the onset of the monsoon [31]. However, NDVI exhibited an inverse trend, with a high value in the post-monsoon and monsoon seasons (0.53–0.62) due to the availability of rainfall for maximum vegetation growth, and a low value in the pre-monsoon season (0.42–0.52) owing to the heat stress and moisture stress in the soil, which is in line with the seasonal vegetation dynamics reported along the Bay of Bengal coastal belt. The spectral salinity index indicated the least negative value (relatively higher surface salinity) during monsoon season which is likely due to more tidal intrusion and saline water inundation from the Bay of Bengal during high flow season as reported earlier by Hossen et al. [32] and Sarker et al. [33] for the low-lying coastal areas of Khulna and surrounding districts. The pre-monsoon and winter seasons on the other hand recorded more negative SI values, which is in line with surface water extent decrease and seasonal drying. The above trend was fairly uniform in all three years of study and this indicates that the land surface dynamics in the coastal Khulna are not merely random but have structural variation.

Table 5. Seasonal mean values of LST, NDVI, NDBI and salinity index (SI) over Khulna district

Year	Season	LST °C	NDVI	NDBI	SI
2002	Pre-Monsoon	28.32173	0.447259	-0.18931	-0.24056
	Monsoon	28.72358	0.531085	-0.30933	-0.11608
	Post-Monsoon	26.14248	0.607285	-0.32952	-0.2423
	Winter	23.85608	0.471109	-0.1861	-0.27799
2010	Pre-Monsoon	29.78338	0.418993	-0.1641	-0.25579
	Monsoon	29.21364	0.531761	-0.32264	-0.12487
	Post-Monsoon	27.21664	0.569231	-0.3564	-0.18711
	Winter	23.48342	0.432054	-0.22118	-0.19899
2020	Pre-Monsoon	30.19341	0.515965	-0.20122	-0.31131
	Monsoon	29.12314	0.616017	-0.31859	-0.15802
	Post-Monsoon	27.24996	0.616759	-0.37081	-0.23286
	Winter	22.76051	0.496217	-0.21673	-0.28093

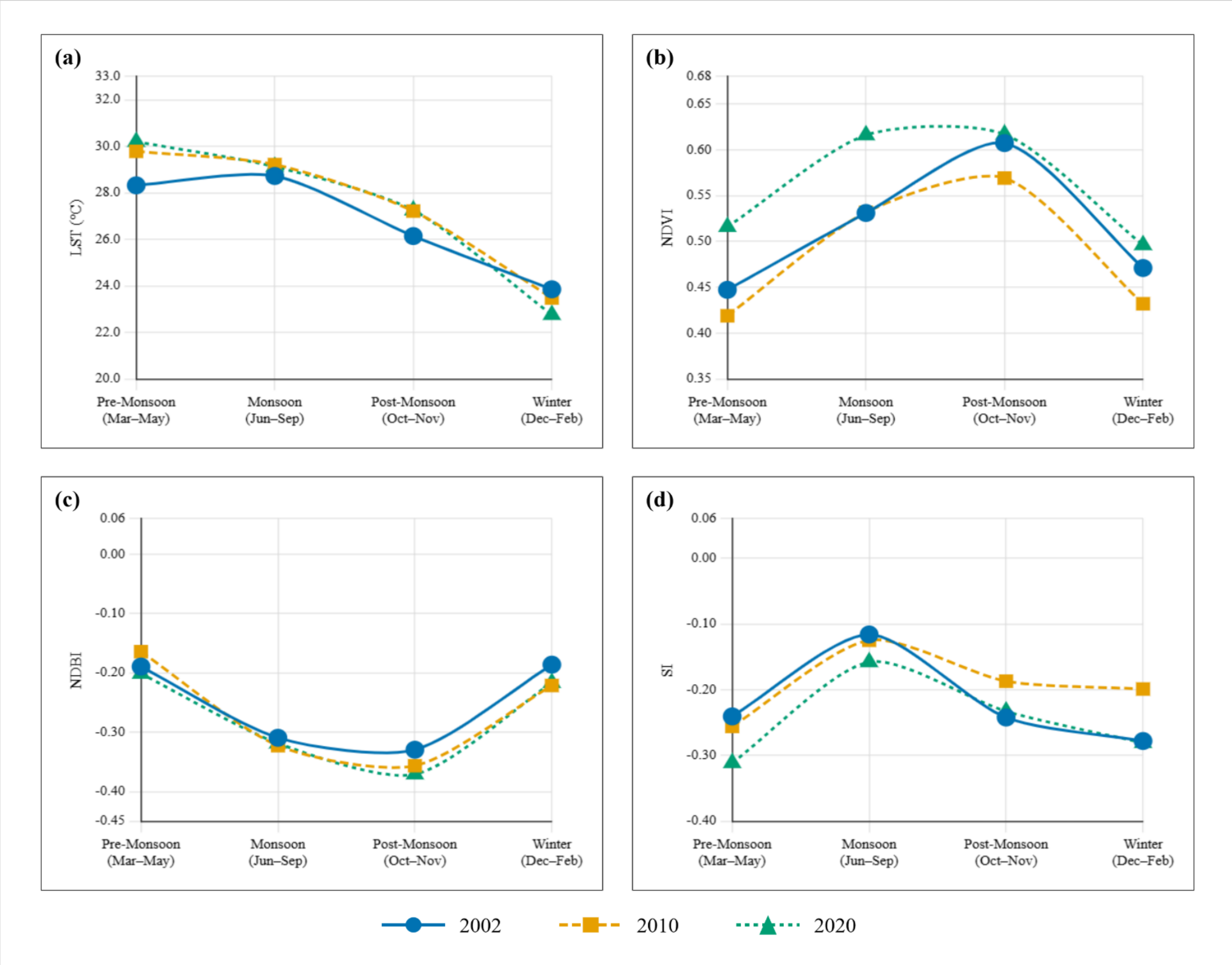


Figure 8. Seasonal variations of (a) LST, (b) NDVI, (c) NDBI, and (d) SI in the coastal region of Khulna

4. Discussion

The findings of this study indicate that the LST dynamics of Khulna District are more related to spatial heterogeneity and land surface characteristics than to a significant long-term warming. The temporal analysis suggests that LST showed a very weak increasing trend of 0.0024 °C yr^{-1} with a statistically non-significant trend time (τ = 0.0435, p = 0.3304), indicating that thermal conditions over districts were relatively stable over the study period. However, spatial analysis of LST maps shows that regions with high temperature are more concentrated in urban and peri- urban regions, indicating thermal intensification in localized regions than in regional warming. A significantly positive NDVI trend (0.0002 yr^{-1}, τ = 0.1365, p = 0.0023) was observed, suggesting that the vegetation condition in the district improved in general which may be attributed to agricultural expansion and afforestation in the periphery. A weak and non-significant correlation (r = 0.0455, p = 0.4964) between NDVI and LST was found, indicating that the greenness of the vegetation at MODIS spatial resolution does not have a significant direct impact on the surface temperature at district level. This limited association may be due to the fact that at MODIS resolution, there are high proportions of mixed land-cover pixels and the spectral similarity between vegetation and other built-up surface types may reduce the net cooling signal from the district level. The relatively poor relationship between NDVI and LST found in this study could be due methodological and ecological factors. However, due to the low resolution of MODIS (1 km), the actual relationship between vegetation and temperature might be masked by the presence of mixing in each pixel, where vegetation is mixed with built surfaces, water bodies, or bare soil; the expected inverse relationship between NDVI and LST may not be true when mixed-pixel heterogeneity is present [34]. Ecologically, the main vegetation of the peri-urban and agricultural land areas of Khulna are the seasonal crops not closed canopy forest. The results indicate a decrease in leaf area index and aerodynamic roughness in croplands, reducing their ability to sustain cooling through evapotranspiration; indeed, globally 60% of croplands even demonstrate a net warming effect relative to the surrounding ecosystems [35]. In addition, research conducted in the agricultural areas of Bangladesh has shown that the NDVI–LST inverse relationship becomes much weaker during crop seasons influenced by monsoon when the influence of atmospheric control factors is high compared to the surface vegetation factors. These dynamics could be better understood with future studies using higher-resolution thermal data (e.g., Landsat-8/9 or ECOSTRESS) and field measurements of evapotranspiration rates.

Despite the negative trend being statistically significant (−0.0002 yr^{-1}; τ = −0.1276, p = 0.0043), this result seems counter-intuitive in light of the known trend of urbanization in the region based on the spectral built-up index (NDBI). This reduction might be due to spectral mixing effect, surface reflectivity difference and the coarse spatial resolution of the MODIS data and might not be a decrease in built-up area. The LST and NDBI were found to be statistically significant but weakly correlated (r = 0.1601, p = 0.0160) with LST variance explained by NDBI being about 2.6% ($R^2 \approx 0.026$), suggesting a slight association of urban surfaces with higher temperatures. NDBI showed a decreasing trend for the study period which may be due to the spectral interference from extensive waterbody and canal system in the Khulna area which is a common feature in deltaic coastal areas as the SWIR reflectance characteristics of water and built-up areas are very similar [36] but the independent evidence indicates significant urban expansion in the area. According to the GHSL [37] built up surface area of Khulna has increased from 25.80 km^2 in 2000 to 45.23 km^2 in 2020, which is 75.4% growth in 20 years. The observed phenomenon of urban expansion is an independently documented phenomenon, which agrees with the land cover changes identified in the present work, providing further context for the observed LST changes. It also proposes that the decrease in the NDBI should not be confused with a decrease in urbanization; it is more likely a result of the known spectral limitations of NDBI derived from coarse resolution MODIS imagery in water-rich landscapes. Spatial analysis results verify that high NDBI values are linked to high LST values, which is as expected due to the properties of impervious surfaces to retain heat. This spatial overlap between LST hotspots and higher NDBI values is seen across all the years analyzed, indicating that the ratio of impervious surfaces plays a role in heat trapping in the hotspots.

The salinity indicator did not exhibit significant temporal trends (τ = 0.0284, p = 0.5263) but does show a clear spatial gradient with high values of salinity index in the spectrum along the southern coast. The statistically significant relationship between the spectral salinity proxy and LST (r = 0.1845, p = 0.0054), which accounts for around 3.4% of the variance in LST ($R^2 \approx 0.034$), indicates that saline-affected surfaces are correlated with higher land surface temperatures in coastal regions. Saline soils may be able to absorb more heat and cool less due to reduced soil moisture availability, limited vegetation cover and changes in surface reflectance but these are only inferred from the current analysis. Although direct field validation with EC measurements was not attempted in this study, the spatial distribution of salinity index value is generally consistent with those found by Soil Resources Development Institute (SRDI) of Bangladesh, in Khulna. Satellite-derived salinity indices for coastal Khulna, as well as several independent studies using SRDI monitoring data, show that salinity is highest during the pre-monsoon season and in the southwestern coastal belt [38]. This spatial and temporal consistency gives some confidence that our Green–SWIR spectral salinity index represents relative salinity gradients between pixels in our study region, but not quantitative accuracy of individual pixels which is a limitation for future field-based studies to resolve.

These results indicate that for the coastal landscape of Khulna, the variation of LST is slightly more correlated to the land-cover configuration (built-up intensity) and the coastal environmental conditions (spectral salinity proxy) than to the vegetation greenness alone. It is important, however, to note that the Pearson correlation coefficients (r = 0.16 for NDBI and r = 0.18 for salinity) are weak in conventional terms and the combined contribution of these two data represents less than 4% of the variance of LST. These relationships are statistically significant, but not substantively strong and should not be interpreted to suggest that there are dominant causal drivers. To more firmly determine the relative roles of these environmental factors in the variability of LST, future studies with multivariate modeling and seasonal analysis and with higher resolution imagery (such as Landsat and Sentinel-2) would be needed. Notwithstanding these results, there are some methodological limitations to recognize. No formal water pixel mask was applied before LST and salinity index (SI) analyses. Mixed land/sea pixel along rivers and canals is inevitable at 1 km MODIS resolution in the coastal deltaic landscape of Khulna, which might affect both the Green–SWIR salinity signal and LST retrieval. Future work should be done with water masking using NDWI or the MOD44W product, and also should take into account the Sentinel-2 (10-20 m) imagery to reduce this contamination. One drawback of this study is that the formal test for serial autocorrelation was not done before the Mann–Kendall test was applied. There is potential for future studies to use modified Mann–Kendall methods to further improve the robustness of trend detection. There were also some uncontrolled confounding factors. In monsoon-dominated areas, SWIR reflectance and LST retrievals would be affected by rainfall, soil moisture, and atmospheric moisture [32]. Trends could be influenced by residual cloud contamination in the monthly composites of MODIS data and by other inter-annual climate variations, such as the number of cyclones and the strength of the monsoon [31]. In the future, the seasonal stratification should be expanded to include the CHIRPS rainfall, ERA5 humidity, and MODIS soil moisture as covariates for more robust analysis, which addresses these concerns. However, the approach of using seasonal stratification in this study is a meaningful improvement on studies with only yearly-scale analysis, as it directly tackles the temporal element of land surface changes in coastal Khulna.

5. Conclusion

Multitemporal MODIS data (2002-2020) were analyzed for the long-term spatiotemporal patterns of land surface temperature (LST) with reference to vegetation greenness, built-up intensity and salinity indicator in Khulna District, Bangladesh. This analysis uses the cloud-based processing in Google Earth Engine, with non-parametric trend analysis and Pearson correlation statistics, to quantify the relationships between surface thermal variability and selected environmental variables in a coastal setting with an open environment.

The key results of the study are summarized below:

- Overall, no long-term trends were observed at the district scale for land surface temperature (approximately 0.002 °C per year; Kendall's τ = 0.0435, p = 0.3304). The monthly LST had a wide range of values from around 20.9 °C to 32.3 °C, with warmer LSTs occurring more often in urban and peri-urban areas.
- The vegetation greenness was significantly increased in the study period (NDVI increased at ~0.0002 units per year, with a τ of 0.1365 and a p-value of 0.0023). Even with this increase, there was still only a low and statistically insignificant relationship between NDVI and LST (r = 0.0455, p = 0.4964).
- There were weak but statistically significant positive relationships between built-up surfaces and LST (r = 0.16, p = 0.016) accounting for ~2.6% of the variance in LST ($R^2 \approx 0.026$). The NDBI trend of −0.0002 per year (τ = −0.1276, p = 0.0043) may be due to spectral mixing or to changes in reflectance, but not necessarily to decreases in urban extent and will need to be confirmed with higher resolution data.
- The spectral salinity proxy did not exhibit significant temporal trends but had weak positive relationship with higher thermal conditions (r = 0.18, p = 0.0054) accounting for around 3.4% of the LST variance ($R^2 \approx 0.034$) and especially in coastal areas.
- In general, the correlations of LST with both built-up intensity and the spectral salinity proxy were weak but statistically significant, indicating that both built-up and the spectral salinity proxy have marginally more measurable relationship with district level thermal patterns than the vegetation greenness. The factors, however, account for less than 4% of the variance in LST, and therefore cannot be viewed as dominant factors. More detailed study is strongly recommended with the use of seasonal data, and higher resolution imagery (Landsat/Sentinel-2) and multivariate statistical frameworks.

Future research can be connected to the seasonality suggested in this study by using higher resolution images and climate auxiliary data to further clarify the environmental dynamics of this sensitive coastal area.

Declaration of Conflict of Interests

The authors declare that there is no conflict of interest.

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