

## **TITLE PAGE**

### **Research Article**

# **Response of land surface temperature with the changes of coastal build-up and vegetation index in the mangrove ecosystem of Chattogram coast, Bangladesh**

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## **Research Article**

### **Response of land surface temperature with the changes of coastal build-up and vegetation index in the mangrove ecosystem of Chattogram coast, Bangladesh**

#### **Abstract**

Mangrove vegetation plays a vital role in habitat and nursing ground for different organisms and prevents coastal erosion caused by wave and tide action. In recent years the mangrove vegetation in Chattogram coast, Bangladesh, has been interrupted by other infrastructural development, which has a destructing effect on the surrounding environment. Land surface temperature analysis of an area helps learn about different environmental conditions, weather, and climate. It is also essential to monitor the rising temperature and global warming, the biggest threat to humanity. NDBI and NDVI are the efficient process for monitoring vegetation and build up areas of a geographical location. This study focused on those analyses to understand the importance of mangrove vegetation in the Salimpur area and surrounding coastal areas of Chattogram by studying the relationship between NDVI and NDBI, NDVI and LST, NDBI, and LST. The outcome indicates that a higher vegetation index results in lower land surface temperature during different periods, negatively correlated. This study also found a strong positive correlation between buildup index (NDBI) and land surface temperature (LST), which means Land Surface temperature was found higher in Buildup areas. The vegetation areas are greatly affected by the buildup areas. The correlation between buildup areas and vegetation areas was strongly negative, which means an increase of NDBI decreases NDVI, and a decrease of NDBI increases NDVI.

**Keywords:** Bangladesh; Land surface temperature; Coastal build-up; Vegetation index; Mangrove ecosystem

## 1. Introduction

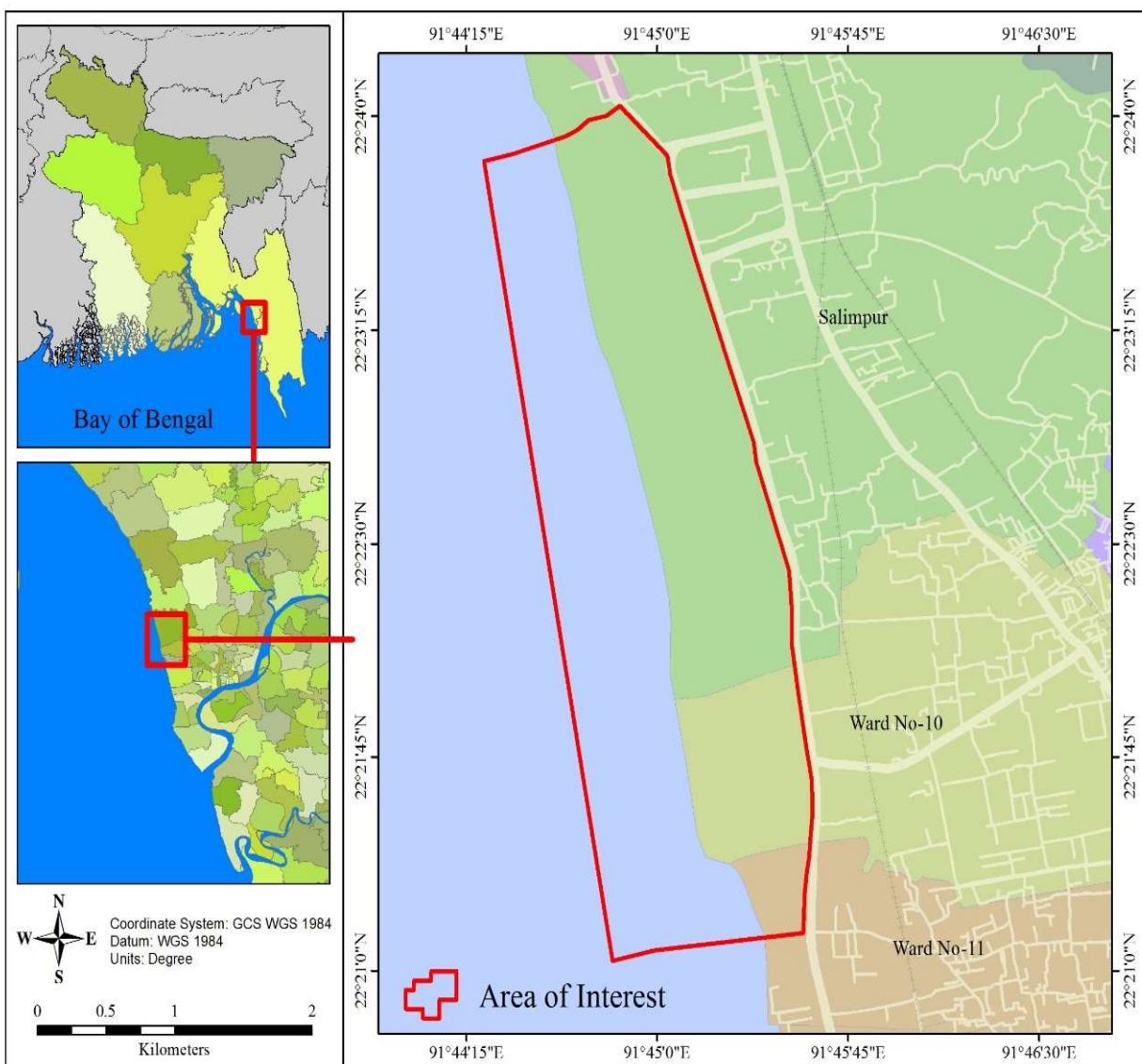
The temperature between the land surface and the earth's atmosphere is known as Land Surface Temperature (LST) [1]. It is frequently employed in all physical parameters, such as balancing the water and energy resources at the interface between the earth's surface and the atmosphere [2]. LST has broad application for assessing vegetation monitoring, soil moisture, evapotranspiration, hydrological cycle, thermal inertia, vegetation water stress, and urban climate [3–5]. It is also used to assess the environment and climate change by observing long-term data [6]. LST is also very effective for obtaining latent heat flux [7]. It is necessary to observe the temperature of various land use/cover and is often used for predicting and checking crop yields [8]. LST has changed in time with vegetation changes, soil composition and topography, and land use land cover [9,10]. Generally, the land surface temperature is measured with remotely sensed satellite data as it is impractical to obtain in-situ data regionally or globally. The remote sensing technique is applied to observe spatiotemporal data such as land cover change and basic physical properties [11]. The surface temperature of different land cover being obtained from satellite-based TIR sensors [12]. LST can also be used to observe forest areas, urban areas, desertification, etc., as it is sensitive to soil moisture and vegetation. Multispectral remotely sensed satellite data provide information for analyzing urbanization and desertification effectively [11]. Vegetation cover has a significant influence on land surface temperature. Vegetation regulates the surface thermal activity through evapotranspiration [13–15], a process by which heat from the air results in the evaporation of water [16]. The most common vegetation index is the Normalized Difference Vegetation Index (NDVI) which is used for assessing the vegetation condition by using the photosynthetic output of a pixel obtained from satellite data [17]. Unlike vegetation cover, the land surface temperature gets influenced by buildup activity on the earth surface. Urbanization mainly occurs when vegetated surfaces are converted into impermeable built-ups, which refers to the conversion of natural surfaces with different artificial settlements such as residential and industrial infrastructures, roads, bridges, and impervious surfaces [18–20]. The transformation affects the humidity in the air, which is influential in land surface temperature change [21].

In remote sensing-based built-up area assessment, normalized Difference Built-up Index (NDBI) is used to determine the built-up areas. In an urban area, the higher NDBI value refers to the urban areas or built-up areas, and the lower value refers to the vegetated areas [22]. Besides higher NDVI value indicates dense vegetation in a vegetated area. Both NDBI and NDVI significantly influence LST [23]; correlation among these indices indicates how urbanization/built-up and vegetation affect the earth's surface thermal activity and relevant environmental phenomenon. So, it is essential to know the correlation information and how these NDBI, NDVI, and LST influence each other. This study aims to assess the correlation among the NDBI, NDVI, and LST at a coastal region of Salimpur mangrove forest in Chattogram, Bangladesh, which has an artificial mangrove forest with 400 acres. In recent years this area has lost its forest due to urbanization and many natural and artificial activities. The current study demonstrates the relationship between NDBI and NDVI, NDBI and LST, NDVI and LST at different years in the Salimpur region. This research and relevant information will open the window for further study on the environmental impact of urbanization, vegetation, and thermal activity of the earth's surface.

## 2. Material and Methods

### 2.1. Study area

The investigation was carried out from November 2016 to November 2020 at the Salimpur mangrove area. The geographical position of the Salimpur mangrove area was latitude  $22^{\circ}15''$  N and longitude  $91^{\circ}49''$  E and about 15km off from Chittagong Port City (**Figure 1**). The study area is about 7.62 sq. km. It is an artificially planted mangrove area situated mainly in the Salimpur union's northern part of the city.



**Figure 1.** Location of the study area of Salimpur mangrove Forest

## 2.2.Data Source

This study used Landsat 8 (OLI) multi-spectral data of post-monsoon for about five years from 2016 to 2020 and was acquired from Earth Explorer to analyze the influence and the relation of the land surface temperature Salimpur mangrove forest with its build-up index variations and vegetation changes. Images used in this study were obtained during November of each sampling year. The dates of data collection were free of clouds and had a clear atmospheric condition. The Landsat images were further rectified to a standard Universal Transverse Mercator coordinate system using ArcGIS Pro. For further analysis, the satellite images provided by Landsat also undergo atmospheric and geometric correction, applied by images processing in ENVI to improve the quality (**Table 1**).

## 2.3.NDBI Analysis

Compared to other surface features, built-up lands have higher reflectance in the MIR wavelength range (1.55 ~ 1.75 $\mu\text{m}$ ) than in the NIR wavelength range (0.76 ~ 0.90 $\mu\text{m}$ ). NDBI is helpful to map urban built-up areas, which is expressed as follows

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad (1)$$

Where NIR is near-infrared reflectance such as ETM+ band 4; MIR is middle infrared reflectance which is ETM+ band 5. NDBI values range from -1 to 1. The greater the NDBI is, the higher the proportion of build-ups [22].

**Table 1.** Landsat data sets that have been used in the study.

Sl. No	Satellite Name	Path/Row	Datum	Projection	Pixel Size	Acquired Date
1	Landsat 8 OLI	136/45	WGS 84	UTM, 46N	30m x 30m	18/11/2020
2	Landsat 8 OLI	136/45	WGS 84	UTM, 46N	30m x 30m	16/11/2019
3	Landsat 8 OLI	136/45	WGS 84	UTM, 46N	30m x 30m	29/11/2018
4	Landsat 8 OLI	136/45	WGS 84	UTM, 46N	30m x 30m	26/11/2017
5	Landsat 8 OLI	136/45	WGS 84	UTM, 46N	30m x 30m	23/11/2016

#### 2.4. NDVI Analysis

The Normalized Difference Vegetation Index (NDVI) is used to quantify the growth and health of the vegetation of an area by computing the spectral reflectance of the surface. Non-Infrared (NIR) and Red bands of Landsat images were used in this study to determine the value of NDVI. The following equation was applied to calculate the NDVI value [24]:

$$NDVI = \frac{NIR - R}{NIR + RED} \quad (2)$$

Where NIR and RED refer to the Near Infrared and Red spectral reflectance value, the value of NDVI ranges from +1.0 to -1.0, and the area with a value of NDVI less than -1 or more excellent than +1.0 is considered a No Data zone.

#### 2.5. LST Analysis

The thermal band is used to convert the raw value into the black body temperature in Degree Celsius using ArcGIS Pro software. The OLI thermal infrared band 10 (10.6-11.19 $\mu$ m) was utilized

to derive the LST. The first step is to convert the DN (Digital Number) values of band 10 to at-sensor spectral radiance using the following equation [25],

$$L_{\lambda} = \left( \frac{L_{max_{\lambda}} - L_{min_{\lambda}}}{Q_{cal_{max}} - Q_{cal_{min}}} \right) \times (Q_{cal} - Q_{cal_{min}}) + L_{min_{\lambda}} \quad (3)$$

Where,

$L_{\lambda}$  = Spectral radiance

$L_{max_{\lambda}}$  = Maximum spectral radiance scaled to  $Q_{cal_{max}}$  in [watts/(m<sup>2</sup> + sr + μm)]

$L_{min_{\lambda}}$  = Minimum spectral radiance scaled to  $Q_{cal_{min}}$  in [watts/(m<sup>2</sup> + sr + μm)]

$Q_{cal}$  = Quantized calibrated pixel value in DN

$Q_{cal_{max}}$  = Maximum quantized calibrated pixel value (corresponding to  $L_{max_{\lambda}}$ ) in DN

$Q_{cal_{min}}$  = Minimum quantized calibrated pixel value (corresponding to  $L_{min_{\lambda}}$ ) in DN

After that, the conversion of spectral radiance to temperature in kelvin [18] is-

$$T_{Kelvin} = \left[ \frac{K_2}{\ln\left(\frac{K_1}{L_{\lambda}} + 1\right)} \right] \quad (4)$$

Where,

$K_1$  = Calibration constant 1

$K_2$  = Calibration constant 2

$T_{Kelvin}$  = Surface temperature in kelvin

Conversion of Kelvin to Celsius,  $T_{(°C)} = T_{Kelvin} - 273.15$ . The calibration constants  $K_1$  and  $K_2$  obtained from Landsat data user's manual (**Table 2**).

**Table 2.** Constants used for the calibration of thermal band.

Satellite	Sensor	$K_1$	$K_2$
Landsat 8	OLI	774.8853	1321.0789

(5)

### 2.6. Correlation Analysis

*Correlation* is a bivariate analysis that measures the strength of association between two variables and the direction of the relationship. In terms of the strength of the relationship, the value of the correlation coefficient varies between +1 and -1. A value of  $\pm 1$  indicates a perfect degree of association between the two variables. As the correlation coefficient value goes towards 0, the relationship between the two variables will be weaker.

The coefficient sign indicates the direction of the relationship; a '+' sign indicates a positive relationship, and a '-' sign indicates a negative relationship. Usually, in statistics, we measure four types of correlations: Pearson correlation, Kendall rank correlation, Spearman correlation, and the Point-Biserial correlation [26].

Pearson r correlation is the most widely used correlation statistic to measure the relationship between linearly related variables. In this study, we will use the Pearson r correlation method. Pearson r correlation is used to measure the degree of relationship between the two [27]. The following formula is used to calculate the Pearson r correlation,

$$r_{xy} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (6)$$

Where,



$r_{xy}$  = Pearson *r* correlation coefficient between *x* and *y*

*n* = number of observations

$x_i$  = value of *x* (for *i*<sup>th</sup> observation)

$\bar{x}$  = mean of the values of the  $x_i$  variable

$y_i$  = value of *y* (for *i*<sup>th</sup> observation)

$\bar{y}$  = mean of the values of the  $y_i$  variable

3. Results

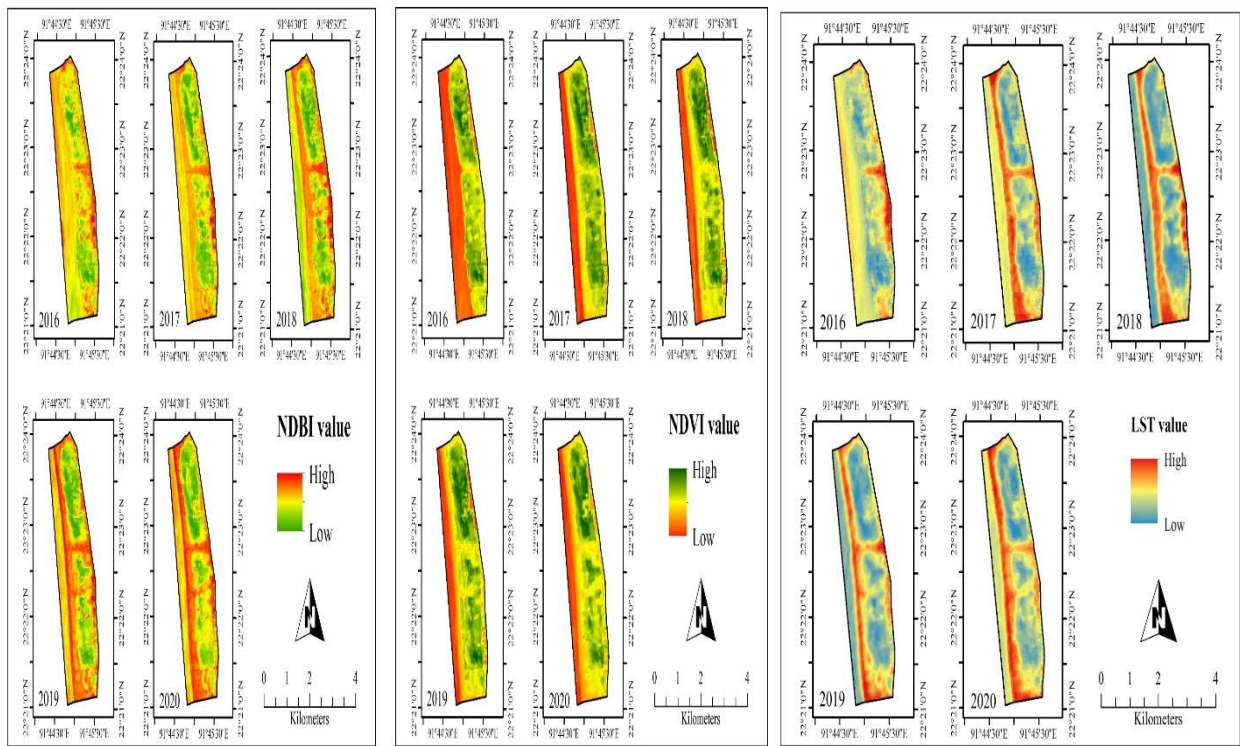
The NDBI values in the study area ranges from -0.390 to 0.126. The lowest build-up index was observed in the year 2019 and the highest value was found in the years 2020. **Table 3** presents the statistical analysis of the NDBI of Salimpur mangrove vegetation for the years 2016 to 2020.

**Table 3.** Statistical analysis of Normalized Difference Build-up Index

	2016	2017	2018	2019	2020
Minimum	-0.296	-0.273	-0.331	-0.390	-0.292
Maximum	0.093	0.072	0.072	0.058	0.126
Mean	-0.107	-0.113	-0.141	-0.153	-0.119
Standard Deviation	0.049	0.055	0.069	0.083	0.060

NDBI value was found almost similar though a red patch of high build-up densities which was found to be formed from the year 2017. The mean values of NDBI showed an increasing trend until 2019 and from then a decreasing rate was observed. The mean values of NDVI for the study area show a positive trend throughout the years where an expansion of vegetation dominated by mangroves, saltmarsh, agricultural activities, and other non-mangrove species was observed

towards the coast in recent years [28]. The vegetation index for the year 2019 shows the highest value of 0.479 and a mean of 0.138 which was 0.069 back in 2016. It can be related to the increase of vegetation throughout the coast as plantations can decrease the accumulated heat in the soil and surface by transpiration [29]. A red patch was observed with newly built up from the year 2017 indicating a gradual rise of temperature in the non-evaporating portion in comparison with its surrounding vegetated, agricultural, and water-logged areas (**Figure 2**).



**Figure 2.** Change of build-up areas, vegetation coverage and LST variation from 2016 to 2020

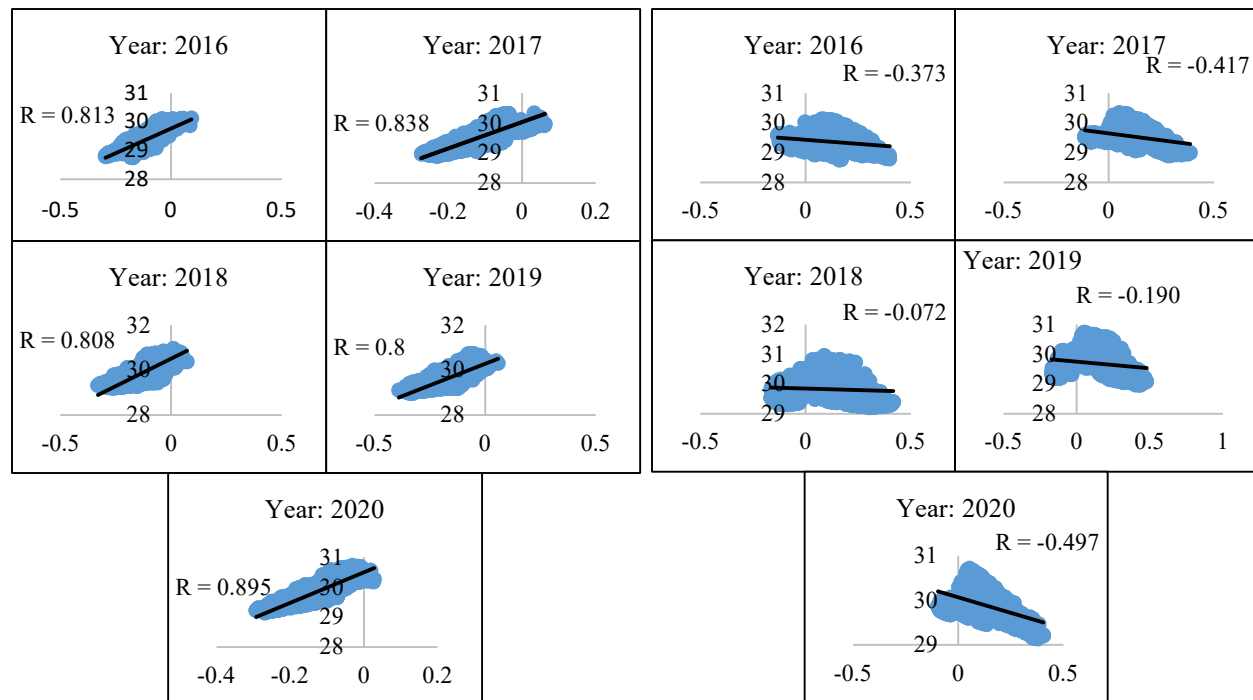
The NDVI values represented the healthiness of vegetation from the years of 2016 to 2020 at the Salimpur mangrove ecosystem (**Table 4**). According to **Table 5**, the land surface temperature was almost constant in the study periods ranging from 28.75°C to 30.95°C. The mean values of LST showed almost same throughout these years.

**Table 4.** Normalized Difference Vegetation Index Statistics

	2016	2017	2018	2019	2020
Minimum	-0.132	-0.113	-0.165	-0.172	-0.096
Maximum	0.399	0.389	0.417	0.479	0.406
Mean	0.069	0.120	0.108	0.138	0.133
Standard Deviation	0.142	0.132	0.144	0.167	0.123

**Table 5.** Qualitative analysis of Land Surface Temperature

	2016	2017	2018	2019	2020
Minimum	28.75	28.88	29.2	28.94	29.14
Maximum	30.14	30.34	30.95	30.75	30.72
Mean	29.4	29.54	29.82	29.69	29.88
Standard Deviation	0.21	0.3	0.42	0.4	0.34



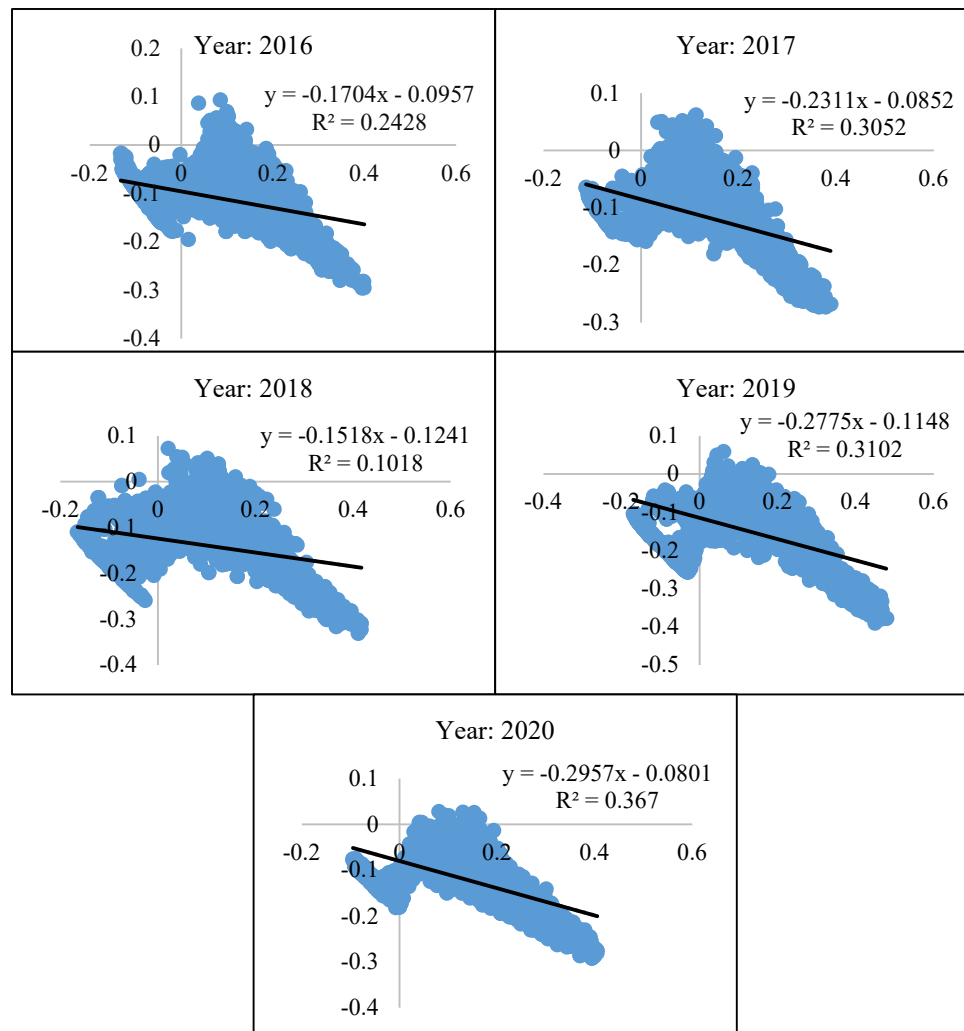
**Figure 3.** (a) Correlation between NDBI and LST. (b) Correlation between NDVI and LST

Correlation between NDBI and LST on different study years (2016 to 2020) is shown in **Figure 3 (a)**. The correlation coefficient showed a consistent, strong, and positive relationship from the year 2016 to 2020 between the built-up area and the land surface temperature. The investigation of the correlation between NDVI and LST is presented in **Figure 3 (b)**. The correlation coefficient between vegetation index and land surface temperature reveals an inverse and inconsistent relation in maximum study years, where in the year 2017 and 2020, a moderately negative correlation was found and in the year 2018 the calculated value was obtained only -0.072 which indicates the weak relation to almost no relation between the NDVI and LST. The relationship between NDBI and NDVI for the year 2016 to 2020 are given in **Figure 4**. Calculated correlation coefficient of this study represents a moderate to essentially strong negative association of build-up index with vegetation index in each year except the year 2018. In the year 2018 the

correlation coefficient value was obtained only -0.319 which revealed a weak negative relationships occurred between NDBI and NDVI in that year.

#### **4. Discussion**

This study deals with the response of land surface temperature (LST) with the changes of Coastal build-up (NDBI) and vegetation index (NDVI) in the Salimpur mangrove ecosystem of Chittagong. The correlation coefficient of NDBI-LST showed a consistent, strong, and positive relationship, which is significant and related to the results of similar studies done in India, China, and Ethiopia [30–32]. The strength and stability of the relationship can be related to the data collection period as all the data were collected mainly from the post-monsoon era [30]. The relationship between vegetation index (NDVI) and surface temperature (LST) of each study year was negative and moderate. This relationship is significant and relevant in the post-monsoon and winter season, supporting the findings of this study [33]. This positive correlation coefficient is also related to evapotranspiration with threshold temperature [34], as the average temperature was higher in these two years. The relationship between NDVI and LST values found in this study is much lower and poor, which can be linked with the urban settlements in and around the study area controlling the land surface temperature variation [35]. A strong negative relationship was found between NDBI and NDVI, which is significant to study the expansion and transformation of built-up areas [11] and plantations and the UHI effect in this vital mangrove ecosystem. Thus, this study revealed that NDBI than NDVI highly influences LST.



**Figure 4.** Relationship between NDBI and NDVI

## 5. Conclusions

Salimpur mangrove vegetation has an impressive effect on the environment of the northeastern coast of Chittagong. This study used Landsat 8 OLI satellite data of the Salimpur mangrove area from 2016 to 2020 to calculate LST and its correlations with NDBI and NDVI. Analysis showed that NDBI and NDVI were negatively correlated where vegetation decreased with the increase of built-up area. Similarly, in the case of the relation between NDVI and LST was also obtained negative. Although the correlation between NDBI and LST was found strong positive, which is

around 0.813 to 0.895. The current study also showed that the influence of NDBI on LST was more potent than the influence of NDVI on LST. This study suggested for future research that the calculated value of NDBI, NDVI, and LST and their correlation may lead to further research to assess the environmental impacts and climate change assessment.

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