Statistical Relation between Vegetation Cover and Land Surface Temperature in Phnom Penh City

Gulam Mohiuddin, Jan-Peter Mund

***Abstract*—**This study assessed the correlation between Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) in Phnom Penh City (Cambodia) from 2016 to 2020. Understanding the LST and NDVI can be helpful to understand the Urban Heat Island (UHI) scenario, and it can contribute to planning urban greening and combating the effects of UHI. The study used Landsat-8 images as the data for analysis. They have 100 m spatial resolution (per pixel) in the thermal band. The current study used an approach for the statistical analysis that considers every pixel from the study area instead of taking few sample points or analyzing descriptive statistics. Also, this study is examining the correlation between NDVI and LST with a spatially explicit approach. The study found a strong negative correlation between NDVI and LST (coefficient range -0.56 to -0.59), and this relationship is linear. This study showed a way to avoid the probable error from the sample-based approach in examining two spatial variables. The method is reproducible for a similar type of analysis on the correlation between spatial phenomena. The findings of this study will be used further to understand the causation behind LST change in that area triangulating LST, NDVI and land-use changes.

***Keywords*—**Land Surface Temperature, NDVI, Normalized Difference Vegetation Index, remote sensing, methodological development.

I. Introduction

URBANIZATION is an inevitable phenomenon in the modern world, and making cities safe, resilient and sustainable is one of the goals of the global partnership between UN member states [1]. Urban areas give a home to more than half of the world population already, and it has a projection to reach 68% by 2050, with a significant increase in Asia [2].

One of the documented climatic effects of urbanization is the increase in both surface and air temperature in the urban area compared to the adjacent rural or peri-urban areas due to a phenomenon termed as UHI [3].

The UHI can affect human health negatively, because exposure to the higher temperature increases blood viscosity and cholesterol level [4]. With the continuous large-scale climate change, the UHI is going to contribute in producing more frequent heat waves [5]. Also, UHI has a connection with increased atmospheric pollution due to intense human activities in urban areas [6].

LST is considered a suitable physical parameter to understand the spatial temperature differences within an urban agglomeration and complex UHI scenario. LST is the skin temperature of the surface that is estimated from the top-of-brightness temperature using the infrared spectral channel of a satellite [7]. It is necessary to separate LST and air temperature based on their physical differences since they are different phenomena that are measured differently. Air temperature is measured at the height of about 1.2 m above the surface. Hence, it varies from the LST.

While urban agglomerations are beneficial to a place in terms of economy and growth but it has an inverted relationship when it comes to environmental qualities [8]. In other terms, the effects of urbanization and UHI will be higher in developing countries [9]. In this context, urban greening has emerged as one of the popular solutions in combating the impacts of UHI. Urban greening can contribute to mitigating the effect of UHI in the area mostly through evapotranspiration [10]-[12].

The relation between vegetation and LST is well established throughout the various literature in terms of both visual interpretation and statistical analysis. An early study was conducted in 1994 investigating the relation between NDVI and LST to identify the surface soil water content where they used NOAH-11 images, and they analyzed the relation using sample areas within their study area in eastern-central Pennsylvania [13]. Another study was conducted in 1997 to detect crop water stress using a digital camera image and a thermal sensor image, where they also used a sample-based analysis [14]. In the same year, a study was published which assessed surface soil water content and energy where they used measurements from the NS001 multispectral radiometer to analyze vegetation and surface temperature. In this study, only mean values of the images taken at different dates and seasons were used in the analysis [15].

Goetz examined a central USA grassland by analyzing NDVI and surface temperature obtained from Landsat Thematic Mapper (TM), taking a few sample plots in that grassland [16]. Surface moisture status was assessed in a study conducted in 2002 in the Northern Senegal that used NDVI and LST obtained from NOAA-AVHRR images re-sampling the pixels into 1 km x 1 km for the analysis [17]. A study conducted in 2004 examined the relation between NDVI and LST to study UHI of Indianapolis, where they use the data from Landsat Enhanced Thematic Mapper Plus (ETM+) and for the analysis, they used a few transects as a sample [18]. A similar study was done in Tabriz urban area in 2009 with the same data source, but it was mostly visual interpretation-based analysis [19]. Another study did a quantitative analysis of LST using different vegetation indices based on Landsat TM data, but it mostly used visual

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interpretation and the comparative analysis of descriptive statistics between LST and different vegetation indices; and the study found a negative correlation between NDVI and LST with a coefficient of -0.78 [20]. A study on estimation of LST over Delhi city was conducted using Landsat-7 ETM+, and after obtaining the LST, they compared it with the NDVI and found a strong correlation in the sampling points applied [21].

One of the objectives of studying vegetation and LST can be assessing the drought scenario that was pointed out in a study in 2004 using MODIS LST and NDVI to develop a drought monitoring system where they showed the comparison in terms of mean values of LST and NDVI collected in different times; and the study found negative correlations between NDVI and LST with a -0.36 coefficient [22]. Another study with a similar objective was conducted in 2004, where they studied the Salt Lake Basin area (Turkey), Landsat-5 images were used obtain LST, and analysis was done based on sample points [23].

In 2015, a study worked on the estimation of the relationship between urban vegetation configuration and LST from Spot image and Landsat TM data where they used different scales to interpret the relation, including a visual interpretation [24]. In 2015, another study was conducted analyzing the LST and vegetation index relation statistically, where they used transect direction as the unit of analysis and LST was obtained from Landsat 5 image; and the study found a correlation efficient -0.46 between NDVI and LST [25].

In a recent study, the authors only visually interpreted the result and used the mean LST and NDVI values to compare on different dates in the year. They found a negative correlation too between NDVI and LST with a coefficient of -0.33 [26].

As it appears, the relation between vegetation and LST is a well-studied topic that can be traced back to 1994 to recent time (2020). Even though every study is different in its way, similarities were found in terms of study objectives and their basis of analysis (sampling-based). It is observed that the relationship between vegetation and LST is studied to assess soil moisture, drought situation and UHI mostly, and the relationship was examined both visually and statistically. But what is noticeable about the statistical analysis is either they considered the mean values of both NDVI and LST or analyzed taking few spatial samples only. Any study that considered the entire study area during analysis is not noticed in the existing literature. Moreover, the existing methods (based on a sample) are producing different correlation intensity (coefficients) that gives a mixed message about the relationship between NDVI and LST.

On this backdrop, this study seeks to use an approach to examine the relation between NDVI and LST in Phnom Penh statistically considering the entire study area instead of using mean values or sample plots. This study also aims to see how the correlation (in terms of coefficient) between NDVI and LST is in the adopted approach and if this relationship can be represented by any statistical model.

The current study is unique in the sense of various ways. Firstly, it used an approach for the statistical analysis that considers every pixel from the study area. Secondly, it has used recent high-resolution thermal data (Landsat 8) and finally, this is examining the influence of vegetation on LST with a spatially explicit approach on this study area (Phnom Penh).

II. Materials and Method

A. Study Area

The study area for this research is the capital city of the Kingdom of Cambodia, Phnom Penh (Fig. 1), adjacent to the Basăk, Sab and Mekong river system [27]. Phnom Penh has more than two million inhabitants and a steep growth rate in terms of population that increased more than 1.5 million in the last 70 years [28]. For administrative purpose, Phnom Penh is divided into City Districts, also known as Khans and Communes, also known as Sangkats. Even though there are in total 105 Sangkats in Phnom Penh, for this study, 80 Sangkats within the Phnom Penh Metropolitan Area are considered [29]. The study area has an area of about 680 sq km.

B. Data and Data Sources

The LST and Landsat OLI 8 data were downloaded from the USGS website using an area of interest based on the extent of the. The data set was selected to download is Landsat 8 OLI/ TIRS C1 Level-1. One of the major challenges for the multispectral images of Phnom Penh is the availability of cloud-free images, which are predominantly available during the dry season from December to April. Objective of this study is to assess remotely sensed data from the period of 2016-2020 (5 years). After looking at all the data available in 2016, it is observed that the 2nd of January has 0.17%, 3rd February has 0.96% and 19th February has 0.12% cloud coverage. To keep the temporal symmetry (anniversary) for comparative discussion for next year's (2017-2020), only images from January and February were checked. In 2018 and 2020, the least cloud coverage images were selected. Even though 2019 has a really low cloud coverage (0.23%) image but unfortunately, that cloud is directly over the study are and affect the LST estimation. Hence, three images from 2016, 2018 and 2020 (January-February) were finally selected for the analysis of this study.

C. Image Processing

Preprocessing of LANDSAT data helps to reduce the solar, atmospheric and topographic effects, including the distortion due to the sensor. LANDSAT Level-1 products are geometrically corrected. In this study, few preprocessing steps are performed such as conversion to radiance and thermal calibration [30].

D. Estimation of LST

The equations in estimating LST are taken from a study conducted in 2016 [31]. NDVI and proportion of vegetation were calculated to calculate the emissivity. Radiance, atmospheric brightness temperature and emissivity were used to estimate the LST (T) (1):

$$T = TB / [1 + (\lambda * TB / C_2) * ln(e) \tag{1}$$

where ‘TB’ is top of atmosphere brightness temperature, ‘λ’ is the wavelength of emitted radiance, ′ C_2′ is [h * c/s], ‘h’ is the Planck’s constant, ‘c’ is the velocity of light and ‘e’ is emissivity.

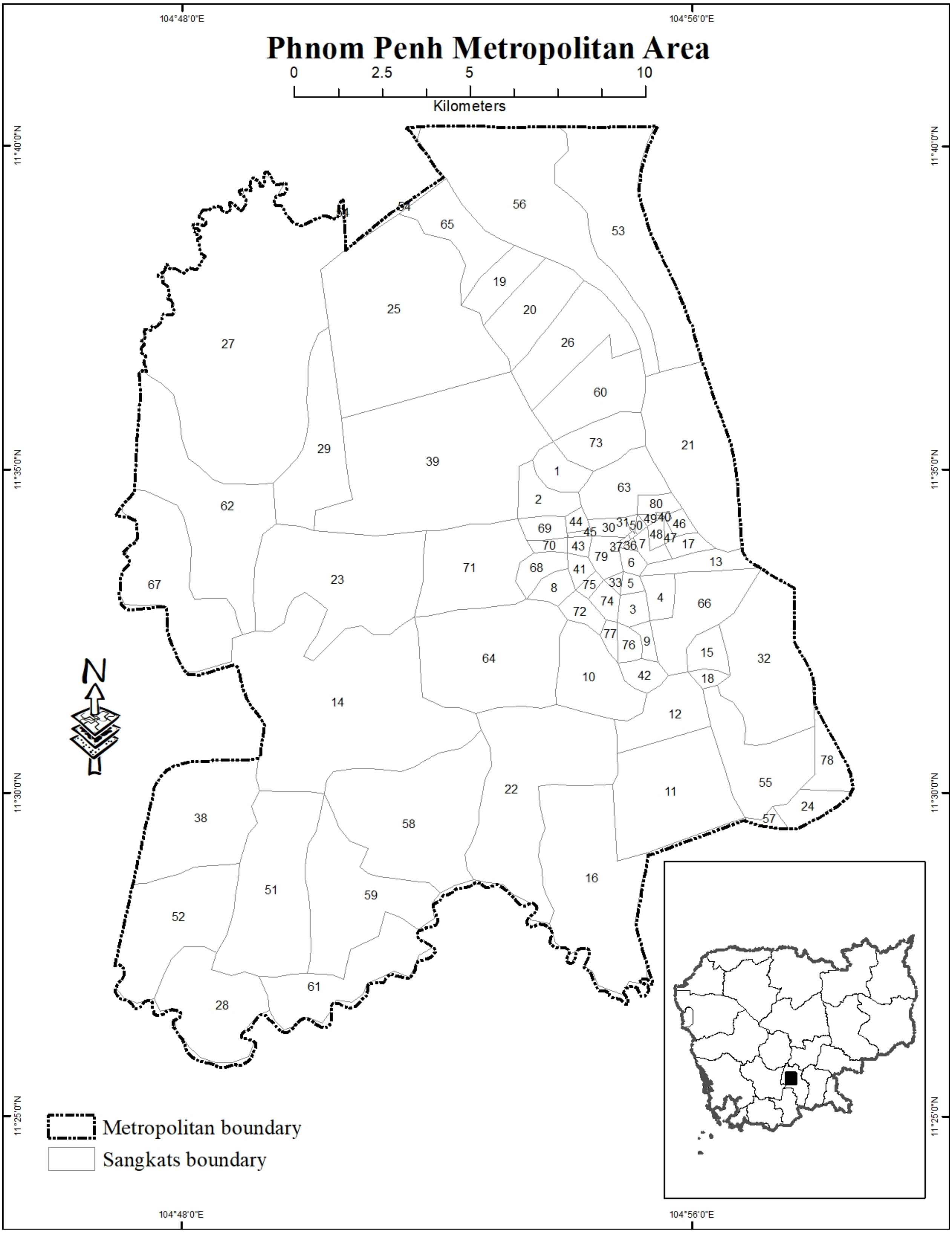
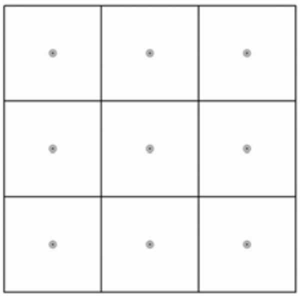
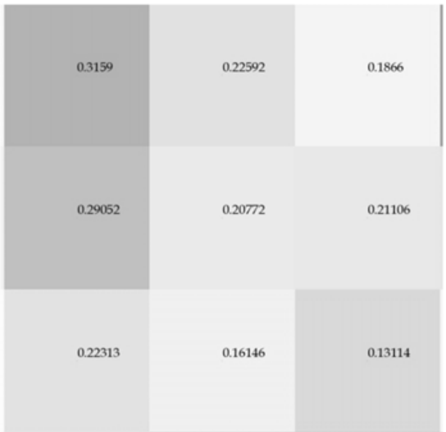


Fig. 1 Study area

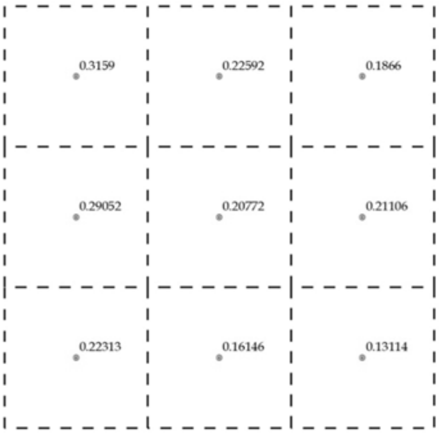
E. Statistical Analysis



(a) Sample empty fishnet



(b) Sample pixel values



(c) Data extraction with centroids

Id	ndvi20	LST20	ndvi18	LST18	ndvi16	LST16
44133	0.22313	20.94892	0.17178	20.17194	0.17458	20.16696
44134	0.16146	20.80587	0.15349	20.239	0.09841	20.0652
44135	0.13114	20.73675	0.14677	20.38534	0.17163	19.97309
44587	0.29052	21.20748	0.16178	20.20424	0.16738	20.40017
44588	0.20772	21.17562	0.17246	20.28115	0.19798	20.27366
44589	0.21106	21.18299	0.2237	20.43479	0.22961	20.18674
45050	0.3159	21.40413	0.19943	20.25878	0.22012	20.56107
45051	0.22592	21.42637	0.18858	20.29105	0.25234	20.44217
45052	0.1866	21.46327	0.21754	20.4348	0.2725	20.36036

(d) Sample of extracted data

Fig. 2 Data extraction process using fishnet (sample representation)

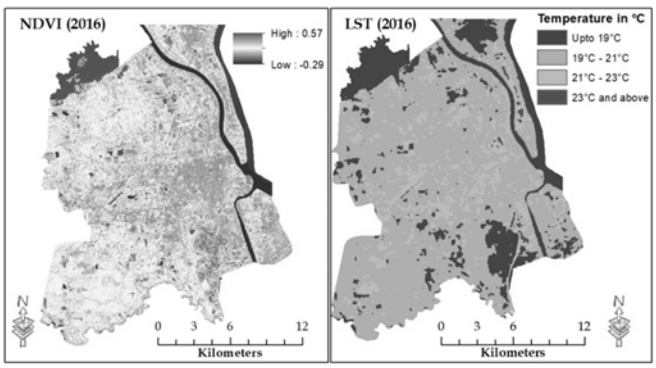
The intended approach aims to extract the pixel values from all the pixels from all the process raster data (NDVI and LST for 2016, 2018 and 2020). In theory, without the pixel values, raster data are a simple fishnet without cell value. Keeping that similarity in mind, a fishnet is created over the geographical extent of Phnom Penh matching the exact pixel boundaries. To create such fishnet with high precision, the starting point of the fishnet was the South-West extent of the original raster. To match the cell size of the Landsat image, the cell size was selected 30 meters. Then a point feature was generated identifying the centroid of each cell of the fishnet. These points were used to extract values from the processed LST and NDVI images (Fig. 2).

To make sure that the analyzed area has vegetation, a subset of the data is created, where the NDVI value is a minimum of 0.24. Besides, the lowest value in NDVI usually indicates water bodies. Hence, using the full data from NDVI will create contradictory statistical result showing a low temperature for both the highest and lowest NDVI values.

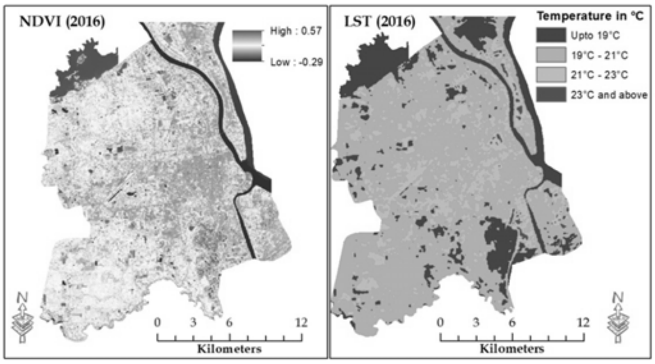
To get a summarized view of the subset data, box plots were drawn that describe the minimum value, the first quartile, the median, the third quartile, and the maximum value. Then the NDVI and LST were plotted in scatter plots, where NDVI is considered as an independent variable, and LST is dependent. Also, to understand the relation between NDVI and LST statistically, Pearson's Correlation Coefficient was determined that provided information about the magnitude of the relationship between NDVI and LST.

III. Results

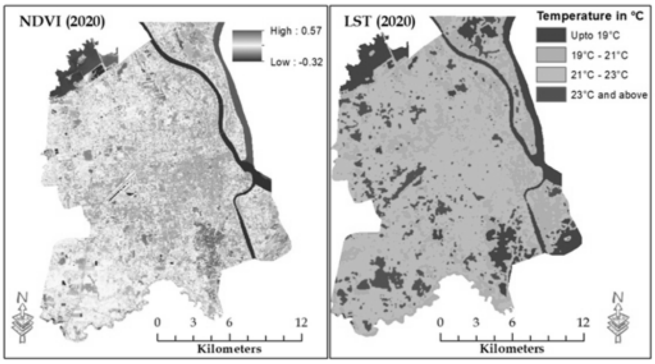
From the visual overview (Fig. 3) of NDVI and LST for all three years (2016, 2018 and 2020), it is observed that the area that has dense vegetation also tends to have a low LST. This relation is visibly prominent in the south-eastern part of the city at both sides of the Bassac River which is open water flooded land or low level depressions which are water-filled during the dry season. Also, it is evident in the north-eastern part of the city between the river channels, which is again a low level of depression or flooded land with dense floating vegetation.



(a) NDVI and LST 2016



(b) NDVI and LST 2018



(c) NDVI and LST 2020

Fig. 3 NDVI and LST of Phnom Penh (2016-2020)

Additionally, it is observed that the study area has an increasing trend in LST in minimum, mean, and maximum values (Fig. 4). Contrary, in the same period, vegetation (NDVI value 0.2 or more) has a decreasing trend in the study area (Table I).

In the case of NDVI, the majority of the data is within the value range of 0.26 to 0.32 in 2016 that range changed from 0.25 to 0.31 in 2018 and 2020 (Fig. 5). This range of NDVI value usually indicates sparse vegetation such as shrubs and grasslands or senescing crops during the beginning of the dry season. LST data show concentration within 20 to 20.45 in 2016 that shifted to 19.5 to 19.95 in 2018 and 20.87 to 21.72 in 2020 (Fig. 6).

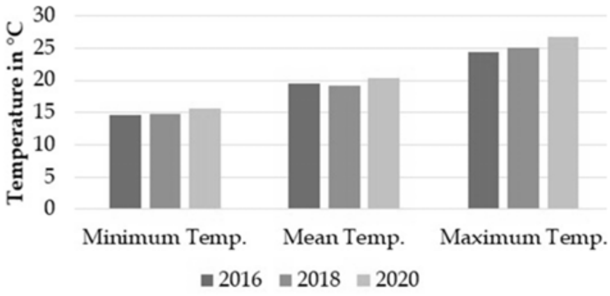


Fig. 4 Changes in LST (2016-2020)

TABLE I
SUBSET OF DATA (2016-2020)

Year	Number of Pixel (=> 0.2 NDVI)	Area (in sq km)
2016	158803	142.92
2018	131304	118.17
2020	104017	93.61

The result of the data subset is processed into a scatter plot considering the NDVI as an independent variable and the LST as a dependent one. From the scatter plot, it is visible that the relation between NDVI and LST is linear in the observed data (Fig. 7). The correlation coefficient between NDVI and LST in these observed data is -0.56, -0.59 -0.57 for 2016, 2018, and 2020 respectively, which indicates a strong negative correlation. This means the higher the vegetation, the lower the surface temperature.

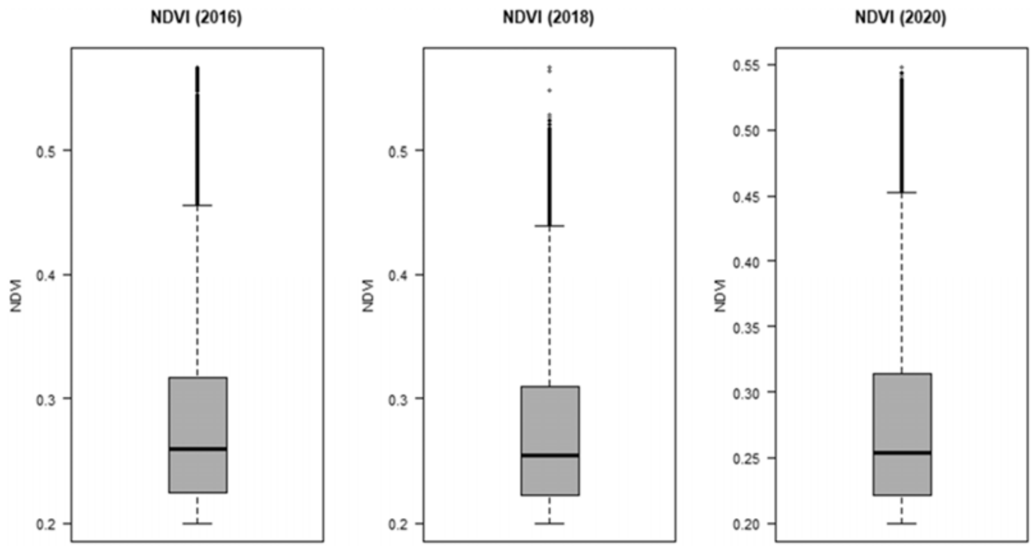


Fig. 5 Boxplots of NDVI (2020, 2018, 2016)

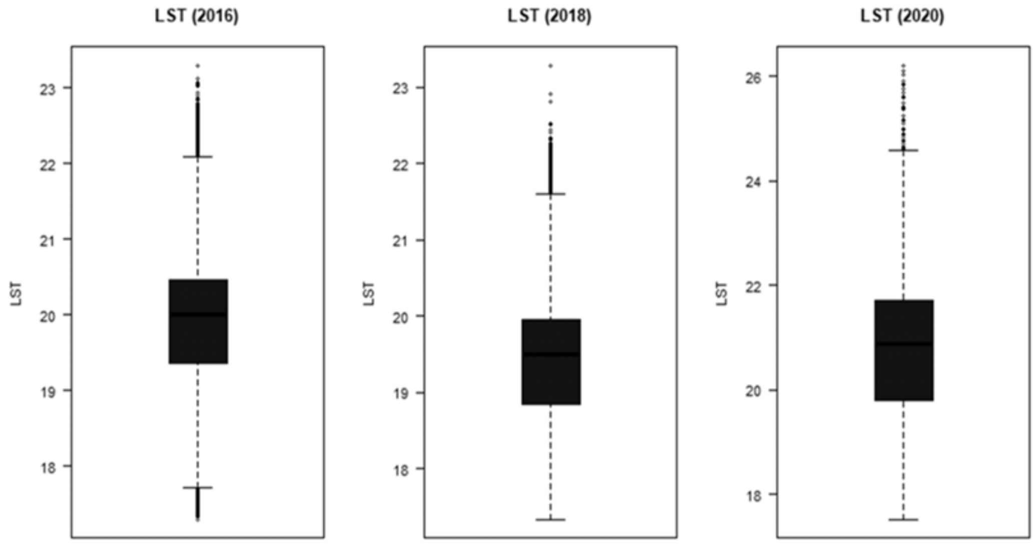


Fig. 6 Boxplots of LST (2020, 2018, 2016)

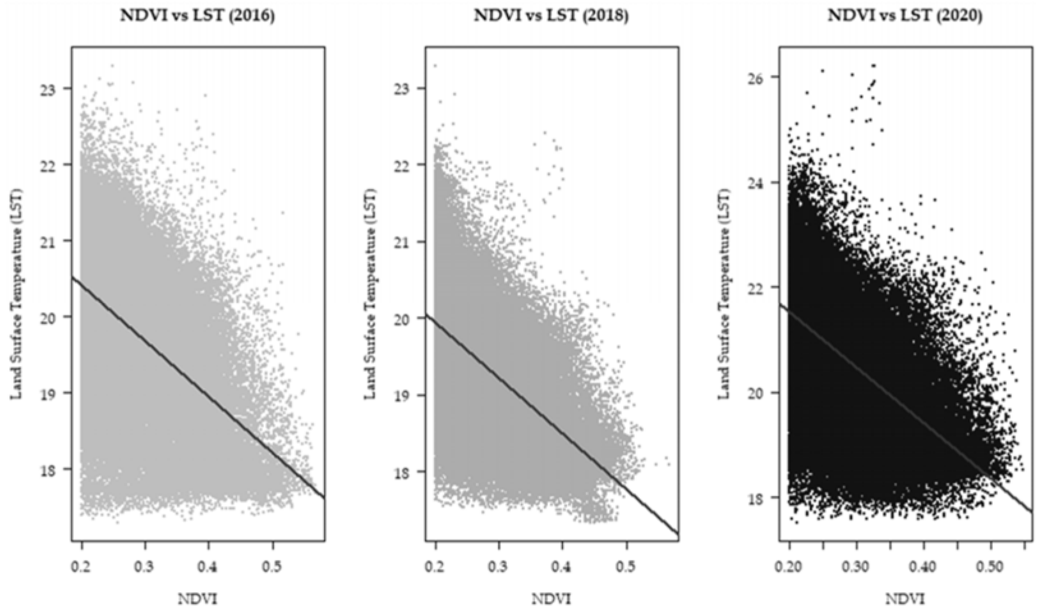


Fig. 7 Scatter plots of NDVI vs LST (2020, 2018 & 2016)

IV. Discussion

The adopted approach of this study addressed the research gap found in the existing literature that either took samples from the respective study areas or used the mean values of different times to express their analysis and produced different correlation intensities in terms of coefficients. This study offers a methodological approach to analyze such relation considering all the pixels in a given study area that removes the possibility of error produced from a sample-based study (e.g. limited selection of samples). The idea that there can be a system of considering all the pixels instead of taking samples is tested, and the study found that there is a strong negative correlation (with a coefficient range from -0.56 to -0.59) between vegetation and LST in the study period, and this relation can be explained through a simple linear regression model.

From the literature review, three key studies are found to be directly related to the statistical analysis between NDVI and LST. The first study was conducted in 2008 in Beijing City in China [20]. The study selected sample pixels from four transect paths with the North-South, East-West, Northeast-Southwest and Norwest-Southeast directions. They used the mean values of both LST and NDVI to figure out the correlation. The study found a strong negative correlation with a coefficient of -0.78.

The second study was conducted in 2015 in Karnataka State in India [25]. The study found a negative correlation with a coefficient of -0.46. However, this analysis comes out from the sample pixels they selected based on two transect paths (north-south and east-west direction).

The third research studied the relation between NDVI and LST in Raipur City in India in 2020 [26]. The study period was from 2002 to 2018. The study took multiple images in the same year and used their mean LST and NDVI values to assess the correlation and found a range of the correlation coefficient of LST–NDVI relationship is −0.18 to −0.49.

All three key-studies discussed here found that there is a negative correlation between NDVI and LST. However, the intensity of this correlation is different and has a wide range of -0.18 to -0.78. These studies used different sampling techniques, and different numbers of areas were considered during the analysis. This difference appears to affect the result significantly. This study addressed this challenge by avoiding the sampling approach and taking the entire area into account.

The study found an additional finding while examining the relation between NDVI and LST. There is a gradual increase in minimum, maximum and mean LST in Phnom Penh City in the study period. Also, there is a gradual decrease in vegetative areas in the same period. It can be further studied by examining the changes in NDVI and LST according to the administrative boundaries (Sangkat).

The data (images) that were analyzed in this study are from January, and February, which is a dry weather season in Cambodia. Hence, the result derived from the analysis is representative of this season only. It would give ideas about other seasons too if images from different seasons are collected and analyzed. However, the challenge is to get cloud-free data in other seasons.

While correlation explains the relationship between two variables, it does not explain causation. To understand the causal explanation behind changes in LST, a further study can be done triangulating vegetation, LST and land-use change in the changed areas.

This study does not undermine the sampling-based previous studies, because sampling is an accepted scientific approach and often convenient in terms of study-time and logistical arrangement. However, this study shows that while examining the spatial phenomena like NDVI and LST, sampling techniques can produce widely varied results in the correlation spectrum. This can give a mixed message about the relationship between NDVI and LST. This study showed an approach to avoid this possible error that might be produced from a sampling-based analysis. This study argues that while the relationship between two variables from spatial data is examined, this approach can be an efficient and less error producing approach.

V. Conclusion

The study adopted an approach where it analyzed the statistical relation between NDVI and LST taking the entire area into consideration instead of sampling techniques like previous studies. This study also discussed and presented how the adopted method can produce less error-free results in comparison to previous key studies. This approach is not limited to understand the relation between NDVI and LST. It can also be used in understanding other spatial relations (e.g. NDWI, SAVI or practically any other spatial indices). With modern computers and analyzing platforms (e.g. R, python etc.), it is now convenient to analyze larger data which makes this approach more convenient.

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