RELATIONSHIP BETWEEN NIGHTTIME LIGHTS AND LAND SURFACE TEMPERATURE

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Abstract: Nighttime lights (NTL) obtained from remote sensing have been used to study the anthropogenic activities on the earth's surface. The intensity of the NTL is associated with human mobility and the characteristics of the land surface. The Land surface temperature (LST) has been used to study the Urban Heat Islands (UHI) and the urban climate change. The LST and NTL varies in accordance with the land cover type and the human activities. Few studies have been reported on the correlation between nighttime LST and NTL. In this study, the influence of nighttime LST with the NTL over the region of Delhi has been analyzed. The NTL (obtained from VIIRS-DNB), NDVI, Land cover and night-time LST (obtained from MODIS) are used to derive a relationship between them. The linear regression and Pearson correlation methods were used in the study and the results show that in 2015 and 2019, the correlation coefficient and R2 value was low between the nighttime LST and NTL at different aggregation levels of land cover (settlements, croplands, other classes) and NTL (low, medium, high light). Additionally, no correlation was found between NDVI and NTL. Using the pixel level correlation of LST-NTL and NDVI-NTL, it has been observed that there is significantly no correlation between the LST and NTL over the urban areas, and neither of the factors considered in the study show a significant correlation with the NTL at the pixel level around the region of Delhi in 2015 and 2019. Hence it was found to be no considerable characteristics and the trends in the relationship between LST-NTL in this study.

Keywords: Nighttime light, Land surface temperature, NDVI, Land cover, Delhi, VIIRS-DNB.

1. Introduction:

This chapter describes the background of the study, motivation and problem statements, research objectives, research questions, and the innovations that are aimed at this research work.

1.1. Background

The human activities have been changing the land surface features of the earth over the years (Gong, et al., 2019), the trends in the change of land surface can be observed through the satellite images, thus the NTL shows the sign of human activities over the region (Proville J, 2017). The NTL is the artificial lighting observed from space through remote sensing. The NTL collected by the satellites contains artificial lights from human activities, lunar contaminations, polar lights, and other atmospheric noise (Elvidge, et al., 2017). It shows the socio-economic development (such as human activities and their footprints) on the earth. The intensity of NTL varies due to several factors including the density of settlements in rural and urban areas, it is evident from the satellite image that there is high intensity around the city centers while low among the rural and vegetated areas. It has been used in a wide range of applications such as estimating population density, estimating the urban extent, and socio-economic information, analysis on global poverty, and greenhouse gas emissions, measuring access to electricity and electrifications and the community resilience. The carbon emissions around the urban areas are mapped using the NTL which depicts the interrelation of socio-economic activities and urban expansions on NTL (Ou, et al., 2015). Studies show that NTL data has a direct relationship with human mobility and power consumption.

The Land Surface Temperature (LST) refers to the radiative skin (top surface on the earth) temperature derived from solar radiation through remote sensing. The LST defines terrestrial thermal behavior at the lower atmosphere on the earth surface, the factors that influence the LST are elevation of the surface, air temperature, clouds, NDVI, population density, Landuse and Landcover (LULC) (Rongbo, et al., 2008). The uneven changes in LST due to human activities lead to Urban Heat Island (UHI), the UHI causes the irregular pattern of temperature variations at the center of the urban spot. The studies on LST and UHI show the response of surface temperature is a function of landcover of a region (Owen, et al., 1998), Since the LST is a measure of thermal radiance from the land surface and surface of the canopy in vegetated areas, it acts as an indicator for energy partitioning and sensitive changes in land surface features. The LST products are used in various research fields such as climatology, hydrology, biogeology, calculating the sea surface temperature.

The previous studies on NTL have focused on the impact of socio-economic activities, urban expansions, population density, and LULC changes on the NTL over a larger area and the significance of the correlation between the variables. The research work on LST examines the influencing factors of surface temperature and gradual increase of LST and UHI over the major cities with spatial and temporal analysis. Considering the importance of the NDVI in studying the NTL and LST, the urbanization effects are quantitatively assessed using the NDVI with NTL (Deng, et al., 2016) the urban centers are mapped using Temperature and Vegetation Adjusted NTL UrbanIndex (TVANU) that combines NTL, LST and NDVI (Zhang & Li, 2018) which shows the interdependency of the NTL, LST and NDVI, the importance of LST and NDVI in detecting the changes in the environment and natural resources, land-use patterns and the vegetations (Chi, et al., 2020).

In this study, the trends, as well as the relationship between the NTL and LST, NTL and NDVI over different land cover classes for a city in 2015 and 2019, along with the analysis of NTL and LST, NTL and NDVI at various level of NTL intensity, so as to analyze the characteristics of the interrelation between NTL and LST, NTL and NDVI. Based on the previous research works the most significant factors that influence the LST and NTL as such as LULC and NDVI are considered for the analysis. The relationship between the NTL and LST and the trends in the association between them is discussed in this study.

1.2. **Motivation and Problem Statement**

The recent studies on NTL focus on the effects of Land cover and the socio-economic factors on the NTL and the relationship between them, the previous works on LST mainly focus on the anomalies in LST along with the urban and human settlements. Hence, it is necessary to find the relationship between NTL and LST along with the trends in NTL-LST for two different years.

Thus, the interrelation of NTL and LST are significant for the prediction of change in NTL using LST and vice versa in the future.

1.3. Research Objectives

The main aim of this study is to find the relationship between NTL and the LST in Delhi and its surrounding. The specific aim is:

- To analyze the characteristics and trends in the relationship between NTL and LST over the region of Delhi.

1.4. Research Questions

The following were the research questions that helped to meet the research objectives:

- Does the LST influence on NTL over the urban area?
- What are the significant factors that influence the NTL?

1.5. Innovation Aimed At

Innovation intended in this study:

- The trends in LST and NTL over the two different periods.
- Our study differs from previous efforts are, we use time series for NTL and LST at the pixel level for all the months in two different years that enables us to compare the trends and the interrelation between them.

2. Literature Review:

2.1 NTL:

Due to the rapid increase in the human population, there is a drastic change in the land surface features over the earth's surface, thus artificial lights are prevalent along with the settlements, industrial areas, and human mobilities such as transportations (Falchi, et al., 2011). Thus NTL data obtained from various remote sensing methods are used as a proxy in measuring the activities of humans (Huang, et al., 2014).

The widely used NTL products are the Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS), Visible Infrared Imaging Radiometer Suite-Day Night Band (VIIRS-DNB) (Elvidge, et al., 2017), and Luojia 1-01 NTL images (Wang, et al., 2020). The VIIRS-DNB provides high-quality low-light imaging over the previous data sources, the VIIRS-DNB data are available from 2012 at a monthly and annual basis, the annual data are free from null values, while in the monthly data there may be null values and atmospheric contaminations such as stray light around polar regions. The stray lights are the unintended lights that enter the sensor which increases the radiance value, thus VIIRS-DNB provides a larger spatial and dynamic range which enables to map of the temporal changes in NTL efficiently (Baugh, et al., 2013).

The recent studies explore the factors that influence the NTL over the urban and rural areas (Jia, et al., 2020), Land-use and land cover type represents the changes in the land surface (Ren, et al., 2020), population density and Human mobility. The NTL data are used to study the different types of urbanization processes and to estimate urban areas using the NTL (Seto, et al., 2013). The urban facilities and population density have more impact on the intensification of NTL radiance observed from remote sensing (Wang, et al., 2020). The NTL plays an important role in the assessment of light pollution, the light pollution occurs in the urban areas where the intensity of the light is high that paves way for the serious health issues and on the environmental resources (Nurbandi, et al., 2016), the assessments natural disaster through the NTL images which are used to compare the affected urban regions (Zhao, et al., 2018).

Based on the pixel-level analysis, the economic variables such as GDP per capita of city level, urban area, and road density which shows a high positive correlation with the NTL. The relationship between the population density and NTL are studied based on high-resolution photographs of ISS to map the population with the NTL (Liu, et al., 2011), here it shows that high positive correlation between the NTL imagery and population density. The intensity of NTL is high among the urban land surface and very low among the areas with forest, cropland and unused lands which are classified based on land cover data, which was derived based on the pixel level analysis (Ma & Ting, 2018).

2.2 LST:

The conversion of land surfaces from natural form to other purposes such as urban use, human settlements creates anomalies in the pattern of local climate which differs from the natural vegetation (Arnfield, 2003). The urbanization is a harbinger of land cover change, destruction of ecology, biodiversity, and the natural vegetations, Urban Heat Islands(UHI), and the hydrological imbalances (Grimm, et al., 2008), the UHI refers to the higher temperature along with the urban centers compared with the rural areas. The UHI is formed due to the anthropogenic heat discharge from vehicles and industries, buildings, reduction in vegetation (Voogt & Oke, 2003). The land cover changes are analyzed using the remotely sensed LST.

The LST data are available from various sources such as Landsat, MODIS, Advanced Very-High-Resolution Radiometer (AVHRR), Aster, etc. The MODIS LST data has been widely used in most of the research works, due to the improved capability of accessibility which is obtained by the split-window algorithm (Mito, et al., 2006) and the day/night algorithm. The NASA's Earth Observing System (EOS) project validates the MODIS LST product which is available at various versions. The recent works on LST products are used to determine the high risk of forest fires since the LST products are available at the various period of daily, 8-day the anomalies in the surface temperature over the forest covers are detected (Mpakairi & Muvengwi, 2019). The urban surface characteristics such as the land cover, vegetation, and the impervious surfaces, and the socio-economic factors have a significant impact on the change of LST along both the day and nighttime (Logan, et al., 2020), The land cover, population density, and the night light are used to assess the temperature differences of a city (Lindén, et al., 2014). The anthropogenic activities such as human mobility, industries, and settlements, change in vegetation influence the surface urban heat island using the LST data (Feng, et al., 2019). The spatial patterns such as NDVI, NDBI, and NDWI along with the POI (the urban land surface categories such as buildings, transport) data that influences LST and the importance of factors (Mustafa, et al., Dec. 2019). There is a significant high positive correlation between the LST and Normalized Difference Built-up Index (NDBI) which implies the direct relation between Surface Urban Heat Island (SUHI), the SUHI represents the temperature difference around the urban and rural areas, thus high negative correlation was found along with the LST and NDVI, where the areas covered by vegetations (Dissanayake, et al., 2019) (Jamei, et al., 2019) (Ma, 2018). The population density and the landcover have a significant impact on the LST based on the spatial correlation between the variables with the LST, along with the correlation between the LST and NTL over the region of China implies there was considerable positive significance between LST and NTL (Li, et al., 2019).

2.3 Research work on NTL-LST:

There are a few recent studies in established the relationship between LST and NTL, which focuses on the characteristics and factors that influence the LST and NTL (L. Li, 2014). The urban built-up areas are extracted by using LST adjusted NTL index along with the POI data, here the POI and LST adjusted NTL urban index (PLANUI) was applied to integrate the POI and NTL to extract the built-up areas (Li, et al., 2020). The urban area mapping through the TVANUI index that combines the NTL, LST, and the NDVI which has the potential of mapping the human activities with these remotely sensed data (Zhang & Li, 2018). The relationship between the NTL and nighttime LST from the previous studies show that there is a comparatively less significant correlation between the NTL and nighttime LST with the correlation between the NTL and daytime LST of a region.

3. Study Area and Datasets:

3.1 Study Area:

The study area, Delhi which is a Union territory and the administrative capital of India. It lies in the northern part of India, the study area extends from 28°53'0"N to 28°24'0" N (latitude) and 76°50'24"E to 77°20'37" E (longitude) (Fig. 1). It lies along the right bank of Yamuna river (India) which covers an area of 1483 km2, the population of Delhi is 19 Million based on 2011 census of India which has been rapidly growing and the city has been expanding every year since people migrate from other states of India in search of a job. The city has a very less forest cover that has been changing every year due to human activities, the forest cover of Delhi increased from 188.77 km2 in 2015 to 195.44 km2 in 2019 from the report of Forest Survey of India, while there is a downward trend in the agricultural lands that have been shrinking drastically over the years. Thus, the irregular pattern of LULC and socioeconomic factors over the region of Delhi is significant for the analysis of LST and NTL in this region. The study area along with the NTL map in Fig. 1.

3.2 Data:

The remotely sensed datasets for the study area the whole Delhi are NTL data, NDVI data, LST data, and Land Cover data. The datasets are obtained for 2015 and 2019 (Table 1). The monthly data of NTL and LST are used to avoid the atmospheric errors and other natural phenomena that hinder the data quality on daily basis.

1. NTL was accessed via the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) global low-light imaging dataset at 500m (15 arc-seconds) spatial resolution on a monthly basis from (https://eogdata.mines.edu/download_dnb_ composites.html). The VIIRS-DNB Band composites version 1 includes the average radiance and cloud-free coverages data. VIIRS-DNB is obtained was at WGS-1984 reference coordinate system. The unit of the radiance value in the NTL data is nanoWatts $cm^{-2}sr^{-1}$.

2. LST data were obtained from Moderate Resolution Imaging Spectroradiometer (MODIS)/Aqua. The average of LST for the 8-day period was obtained from MYD11A2 V6 which has a spatial resolution of 1000m. The 8-day composite period has an advantage of the repeated ground track of the satellite over the region in case of less coverage due to cloud coverages at a specific time. The units of the LST data are Kelvin (K). The LST data is available at the MODIS-Sinusoidal projection at a global extent. The LST is a 16-bit unsigned integer and the value ranges from 7500 to 65535 with a scaling factor of 0.02.

The cloud covers and other atmospheric corrections are made in the down-sampled data that are available in the MODIS.

3. NDVI data were obtained from MODIS/Aqua from the MYD13A2 version 6 product which is at a spatial resolution of 1000m. The NDVI is related to the continuity index of the existing National Oceanic and Atmospheric Administration-Advanced Very High-Resolution Radiometer (NOAA-AVHRR) derived NDVI. The NDVI data is available at a 16-day period in MYD13A2 product at MODIS-Sinusoidal projection for global extent. The valid range of NDVI data is -2000 to 10000 with the scaling factor of 0.0001, the NDVI has no units. The 16-day composite version 6 is generated from two 8-day composite surface reflectance granules.

4. Land Cover (LC) data were obtained from MCD12Q1 V6 product which is at a spatial resolution of 500m. The MCD12Q1 version 6 product is derived from the supervised classification of MODIS Terra and Aqua reflectance data. The LC data is available at MODIS-Sinusoidal projection on yearly basis. The LC_Type1 (International Geosphere Biosphere Program (IGBP) classification system) is obtained which is an 8-bit unsigned integer and the values range from 1 to 17. In the current study area, the land cover classes are Savannas, Grasslands, Permanent Wetlands, Croplands, Urban & Built-up Lands and Water Bodies, respectively. These classes are further recoded into 3 classes as shown in Table.2.

Table. 1 Description of data products

	Resolution(m)	Projection	Band	Time-Period
NTL	500	WGS-1984	avg_rad	Monthly
LST	1000	MODIS-SINUSOIDAL	LST_Night_1km	8-Days
NDVI	1000	MODIS-SINUSOIDAL	NDVI	16-Days
LC	500	MODIS-SINUSOIDAL	LC_Type1	Yearly

Table.2 Land covers classes

IGBP Land cover	Recoded Land cover	Description
Urban & Built-up Lands	Settlements	Areas that have human settlements and populated with industrial and commercial facilities
Croplands	Croplands	Areas covered with cultivated crops and agricultural lands
Savannas, Grasslands, Permanent Wetlands, and Water Bodies	Other classes	Areas covered with Grasslands, forest, Wetlands, and Waterbodies

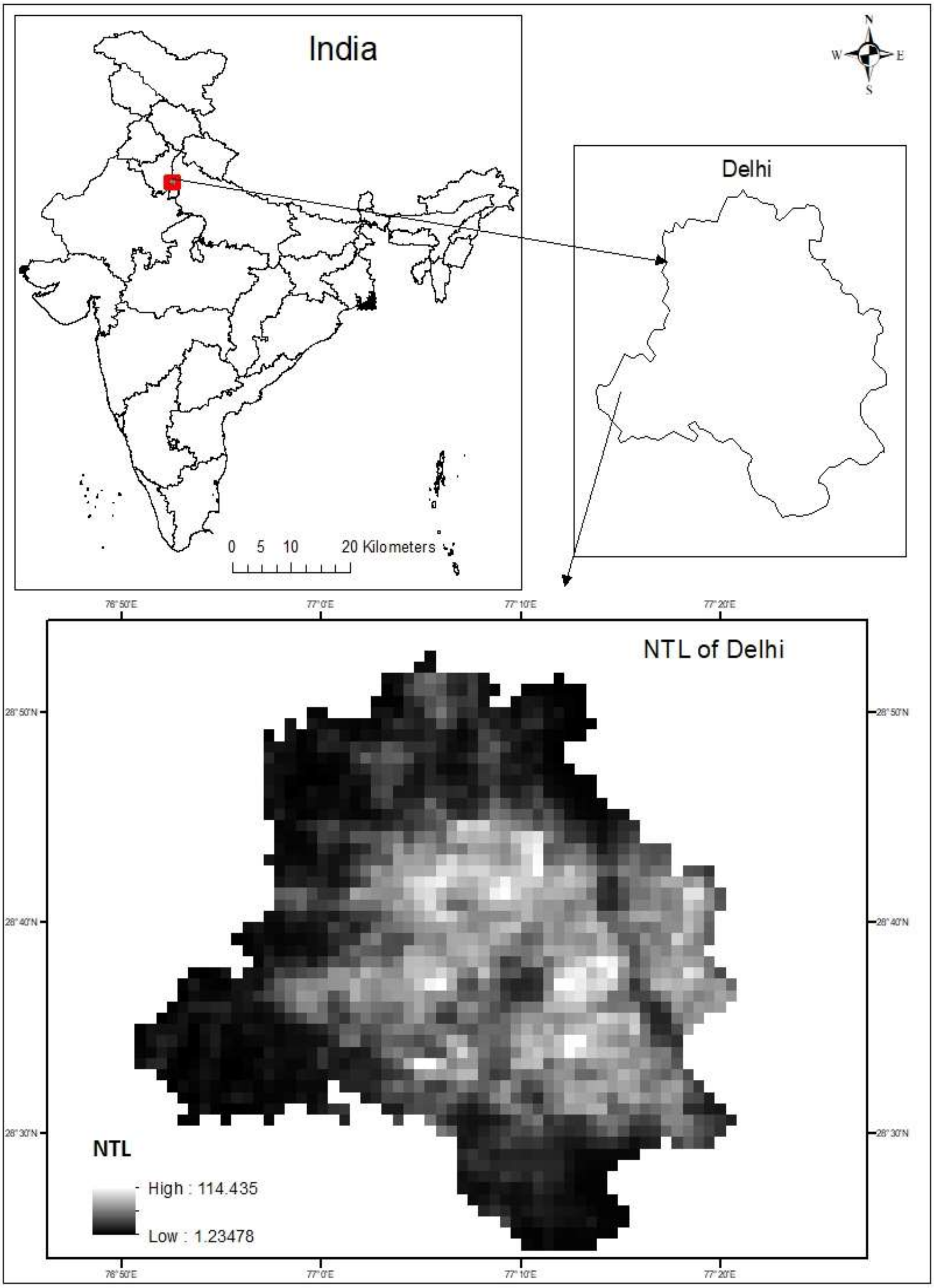

Fig. 1 Location and NTL image (May 2015) of the study area: Delhi, India

4. Methods:

The overview of the methodology is explained in a flowchart (Fig.2), which shows the data and process of analysis.

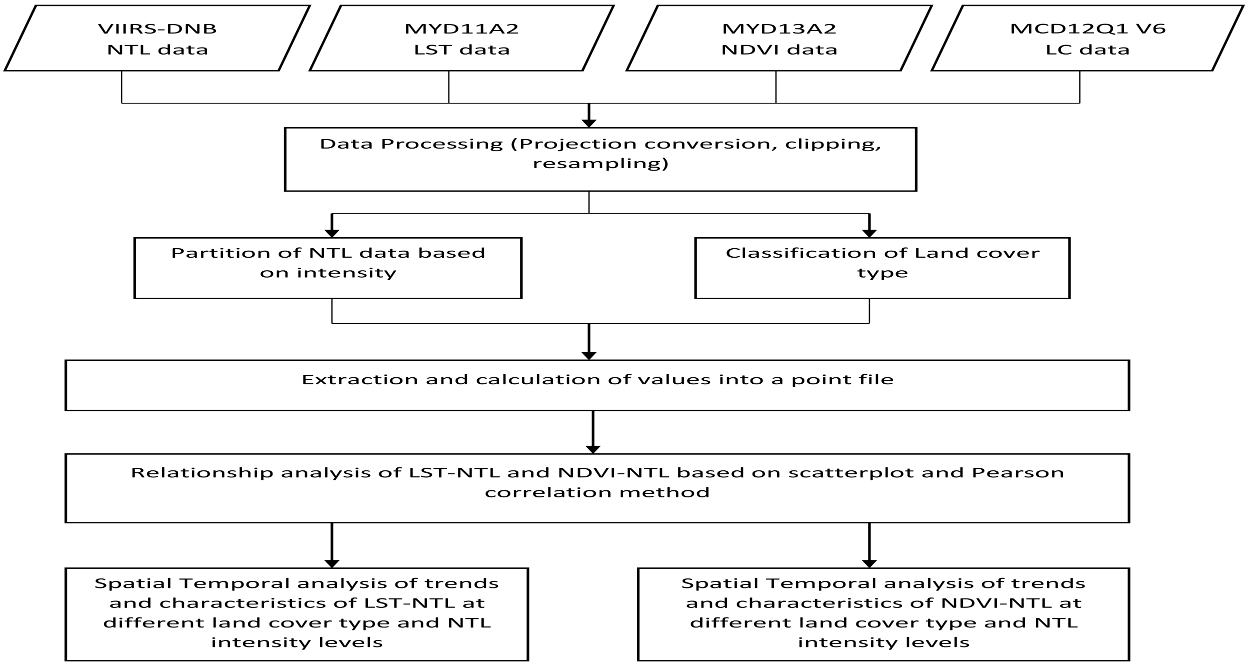

Fig.2 Workflow of this study

4.1 Data Pre-processing:

1. NTL data derived from VIIRS-DNB products are at 500m resolution, thus to perform the analysis, the NTL data were resampled to 1000m spatial resolution, here the Bilinear interpolation using the resampling tool that is available in ArcGIS software, the Bilinear interpolation is being used for the continuous data consist of the floating-point values. The value 0 represents the absence of artificial lights which is around the rural area and high intensity represents more settlements in the urban area.

2. LST data of nighttime over the study area was obtained from MYD11A1 on the 8-day basis and downsampled to monthly (2015 and 2019), the mean of the 8-day data are used to calculate the monthly by avoiding the null values that occur in the downloaded data due to the various atmospheric parameters at the time of satellite coverage over the surface. The scaling factor for the LST data which are available in the documentation of MODIS products has been used to calculate the actual temperature of the surface, here the scaling factor 0.02 was multiplied with the DN value of the data. Thus, the calculated temperature values are in Kelvin(K). The LST data from MYD11A1 is available at MODIS-Sinusoidal projection, hence it is re-projected to WGS-1984 for processing.

3. NDVI data accessed from MODIS (MYD13A2) are obtained for 16-day basis, which is down-sampled to monthly, thus the mean of the 16-day dataset are used to generate the monthly data. The scaling factor for NDVI data is 0.0001, which is multiplied with the raster value to get the NDVI (ranges from -1 to +1) for the vegetation type. The NDVI data in MODIS-Sinusoidal Projection are re-projected to WGS-1984 for analysis.

4. Land Cover data were obtained from MODIS land cover type (MCD12Q1) version 6 for 2015 and 2019. These data are available in MODIS-Sinusoidal Projection which was converted to WGS-1984 reference system.

4.2 Partition of NTL intensity level and land cover classes:

1. The NTL data over the region of Delhi consists of high-intensity radiance value due to the high population density and the settlements along with the less vegetation cover. Thus, the intensity of the NTL data is classified based on the specific range of values the low light NTL with the range of 0-10, medium-light NTL with the range of 10-25, and the high light NTL which are above 25. The NTL values are partition into three levels for 2015 and 2019 which was used for the analysis.

2. The Land cover data for the Delhi consists of the different classes which are obtained from LC_Type1 ranges from classes 9-13, thus classes 9,10,11,12,13 are savannas, grasslands, permanent wetlands, croplands, and urban and built-up lands respectively for 2015. These are reclassified as settlements, croplands, and other classes (contain the savannas, grasslands, and permanent wetlands). For the year 2019, there are savannas, grasslands, croplands, urban & built-up lands, and water bodies. These are reclassified as settlements, croplands, and other classes (savannas, grasslands, and water bodies).

3. Based on the comparison of land cover types in 2015 and 2019 the spatial distribution of different land cover classes (Fig. 2), the settlements have increased to a certain extent while the croplands have reduced considerably. The NDVI data distribution around the region of Delhi is shown in Fig. 2. The spatial distribution of NTL levels such as low light, medium light, and high light after classification for May in 2015 and 2019 shows the increase in the high light and medium-light areas over the suburban areas and rural areas respectively which are interpreted visually (Fig. 3), the LST values comparison for 2015 and 2019 shows the spatial distribution of the temperature, which depicts the high temperature over the center (urban) and low among the rural and sub-urban areas (Fig.3).

4.3 Correlation model for NDVI and LST with NTL:

The correlation between LST and NDVI with NTL for different land cover types and the NTL level was developed based on the previous works to analyze the trends and characteristics between them. The analysis was performed at the pixel level value of the available considered, the average of the NTL, NDVI, and LST are computed for 2015 and 2019. Thus, the relational model for different NTL levels and land cover was developed which shows the trends and characteristics of NTL. The Pearson correlation method was used to find the correlation coefficient (R) which determines the relative significance between the dependent and independent variables in this study. The R varies from -1 to +1 and it is stronger when moving away from zero, the -1 indicates that if one variable increases the other tends to decrease while the +1 indicates that if one variable increases the other variable also increases and the zero represents the no correlation between the variables. In this way, the linear relationship between two variables can be established.

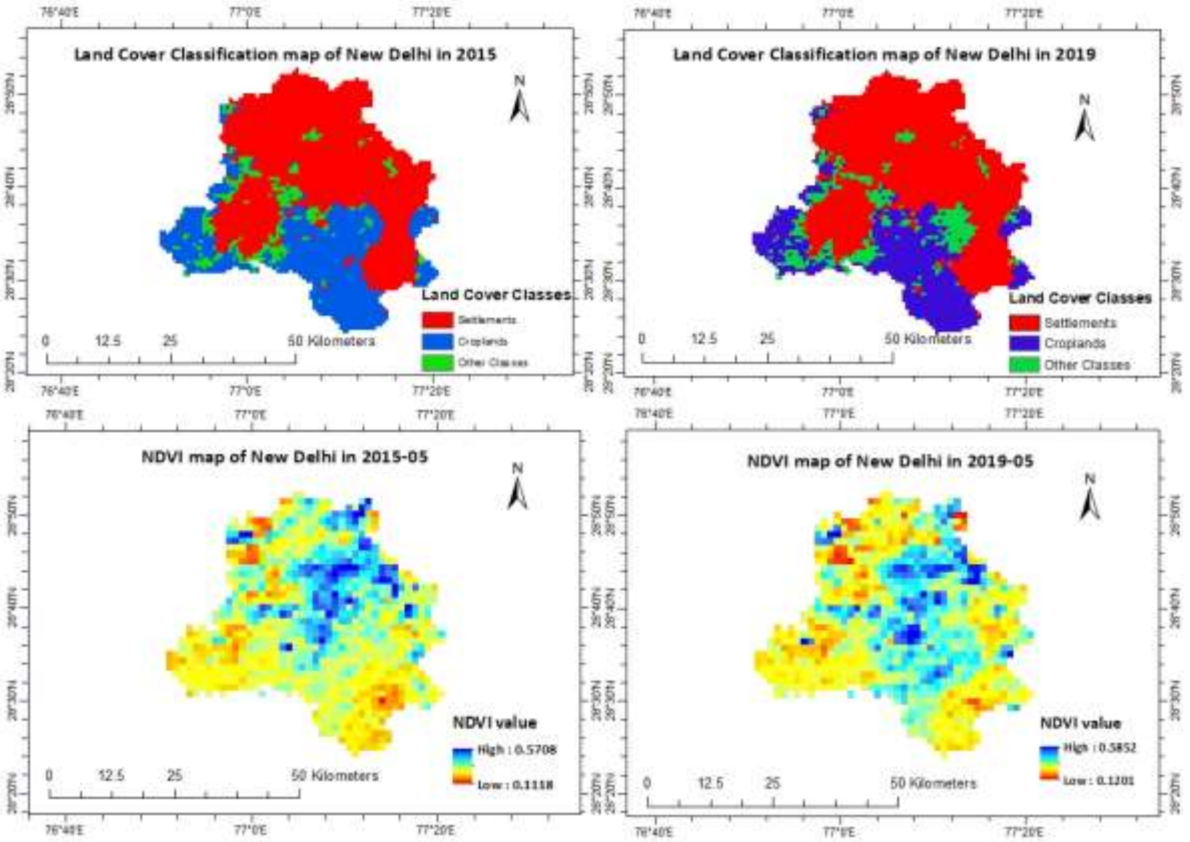

Fig. 2 Land surface cover and NDVI images for New Delhi.

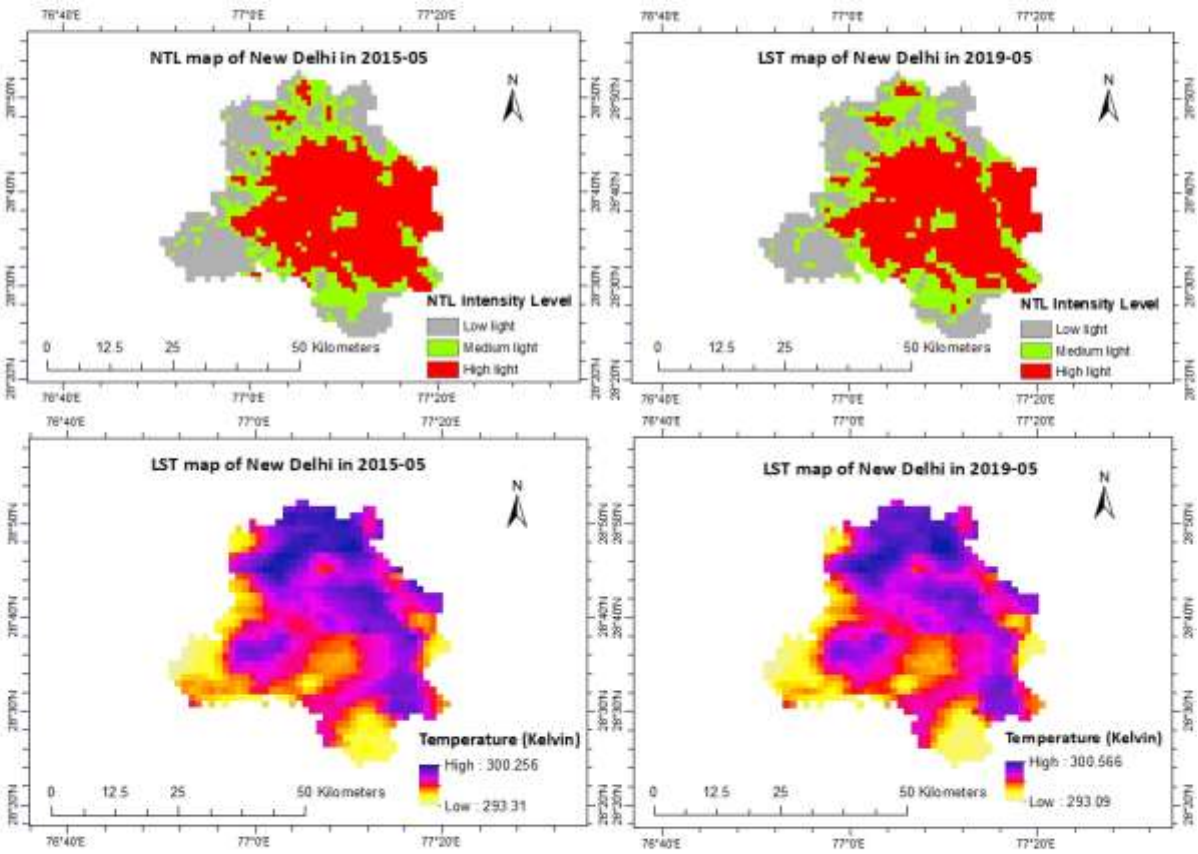

Fig. 3 NTL and LST images for New Delhi.

5. Results:

5.1 Relationship between LST and NTL:

The linear regression of LST and NTL for settlements, croplands, and the other classes for the 2015 and 2019 shown in (Fig. 4). The coefficient of determination (R^2) of the LST-NTL for the area of the settlement in 2015 and 2019 are very low and the regression line shows the downward trend which and the comparatively low slope values depict the weak relation between the LST and NTL for the settlements areas. The temperature varies from 289.41 to 294.42 in 2015 while it was 289.97 to 294.25 in 2019, which shows the irregular change in the temperature of the region. For the areas with croplands, the temperature varies from 289.07 to 292.80 in 2015 and the minimum and maximum temperature in 2019 are 289.35 and 292.82 which shows the gradual increase in minimum temperature of the areas with croplands. The temperature along the other classes in the land cover type for the study area is from 289.65 to 293.39 in 2015, while it varies from 289.60 to 293.22 in 2019 which shows the decrease in the minimum and maximum temperature.

The linear regression of LST and NTL for a different level of NTL light intensity are plotted to analyze the influence of LST over NTL (Fig.5). There are three levels of light intensity low light, medium light, and high light, thus the scatterplot of the LST and NTL shows the R^2 along with the slope of the linear equation. The slope of the regression line shows the rate of change in NTL for the change in LST. From the R^2 values of different night levels, there is no significant correlation between LST and NTL. The temperature varies of LST at nighttime varies from 289.07 to 294.42 in 2015 along with the areas of low light level, while it varies from 289.35 to 294.25 in 2019. The temperature variation among the medium-light areas were 289.18 and 294.27 in 2015, while it varies between 289.41 and 294.11 in 2019. The maximum and minimum temperature over the areas with high light intensity were 289.76 and 294.27 in 2015 and it varies from 289.82 to 294.11 in 2019.

5.2 Relationship between NDVI and NTL:

The relationship between NDVI and NTL are analyzed based on the scatterplot of two variables, the dependent variable (NTL) along the y-axis and the independent variable (NDVI) along the y-axis (Fig. 6). The regression line and the R^2 shows the relationship among the variables, the slope of the linear equation shows the influence of NDVI on NTL, where the high slope values indicate the greater influence of NDVI on NTL. The scatterplots of NDVI with NTL at different land cover classes for 2015 and 2019 are used to analyze the characteristics of the NTL with the NDVI (Fig.5). The NDVI values for settlements, croplands, and other classes in this study area vary from 0.5284 to 0.1092, 0.5102 to 0.2236, and 0.5079 to 0.2074 respectively in 2015. The maximum NDVI value for settlements, cropland, and other classes were 0.5502, 0.5192, and 0.4752 in 2019, respectively. Thus, based on the NDVI value for 2015 and 2019 on different land cover classes it is evident that the vegetation cover along the settlements and croplands classes are on the increasing trend and the other classes show a downward trend.

The NTL levels which are classified based on the intensity of light are used to analyze the relationship between the NDVI and NTL (Fig.6). The average values of each pixel for 2015 and 2019 are calculated and the scatterplot of NDVI and NTL at each level of light intensity is plotted, which shows the slope and R square values that are used to establish the relationship among them. The NDVI value greater than 0.5 shows the moderate vegetation cover and less than 0.2 shows the less vegetation and barren lands. The maximum NDVI value in 2015 for high intensity pixel regions, the medium, and low lights were 0.5502, 0.4980, and 0.4929, respectively. The maximum values of NDVI in 2019 were 0.5282, 0.4859, and 0.4883 for high, medium, and low light levels, respectively. Thus, there is a growth in the vegetation cover along the region from 2015 and 2019 for high and medium light levels and considerably less change in low light levels.

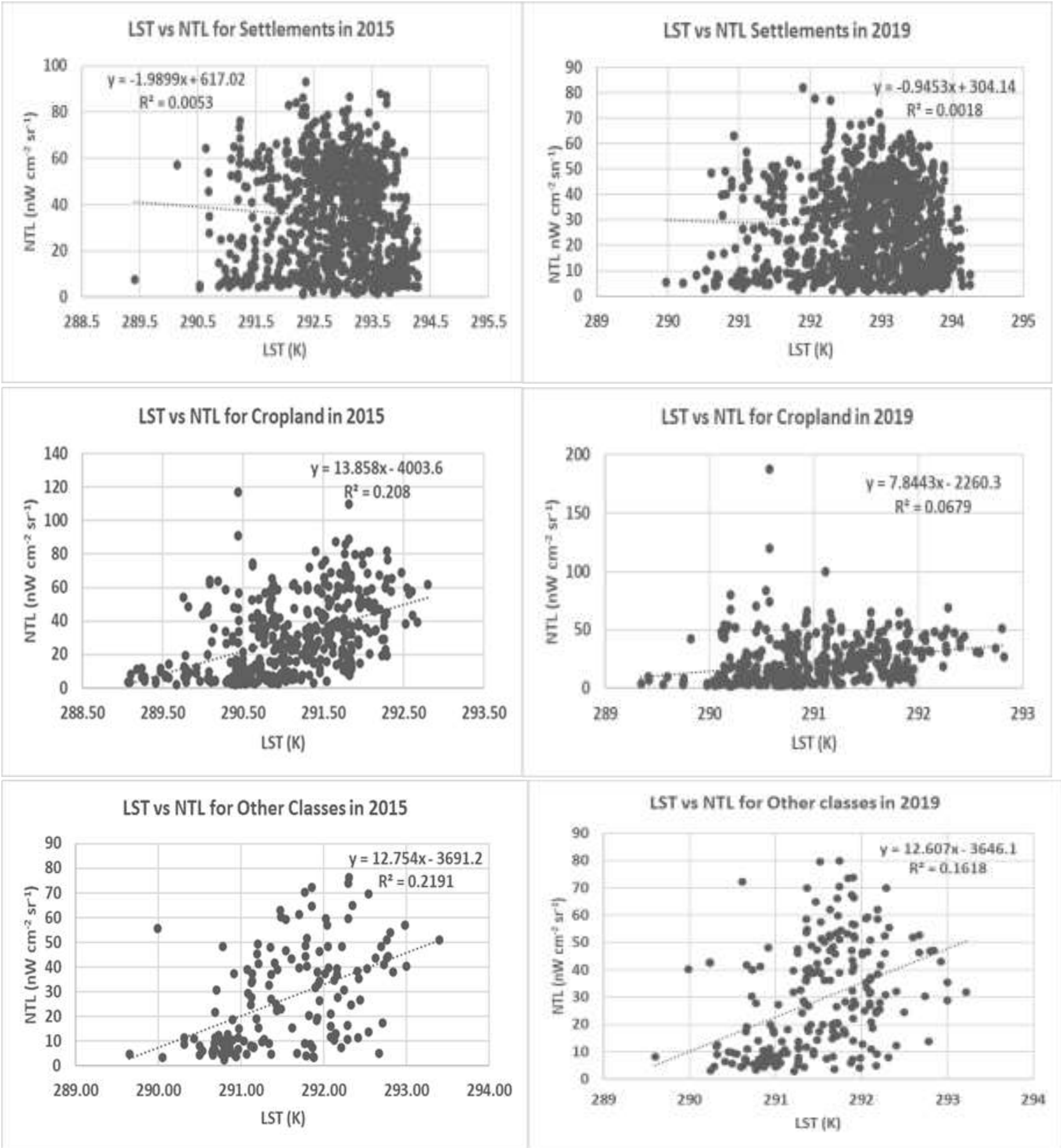

Fig.4 Scatterplot of LST- NTL for land cover type

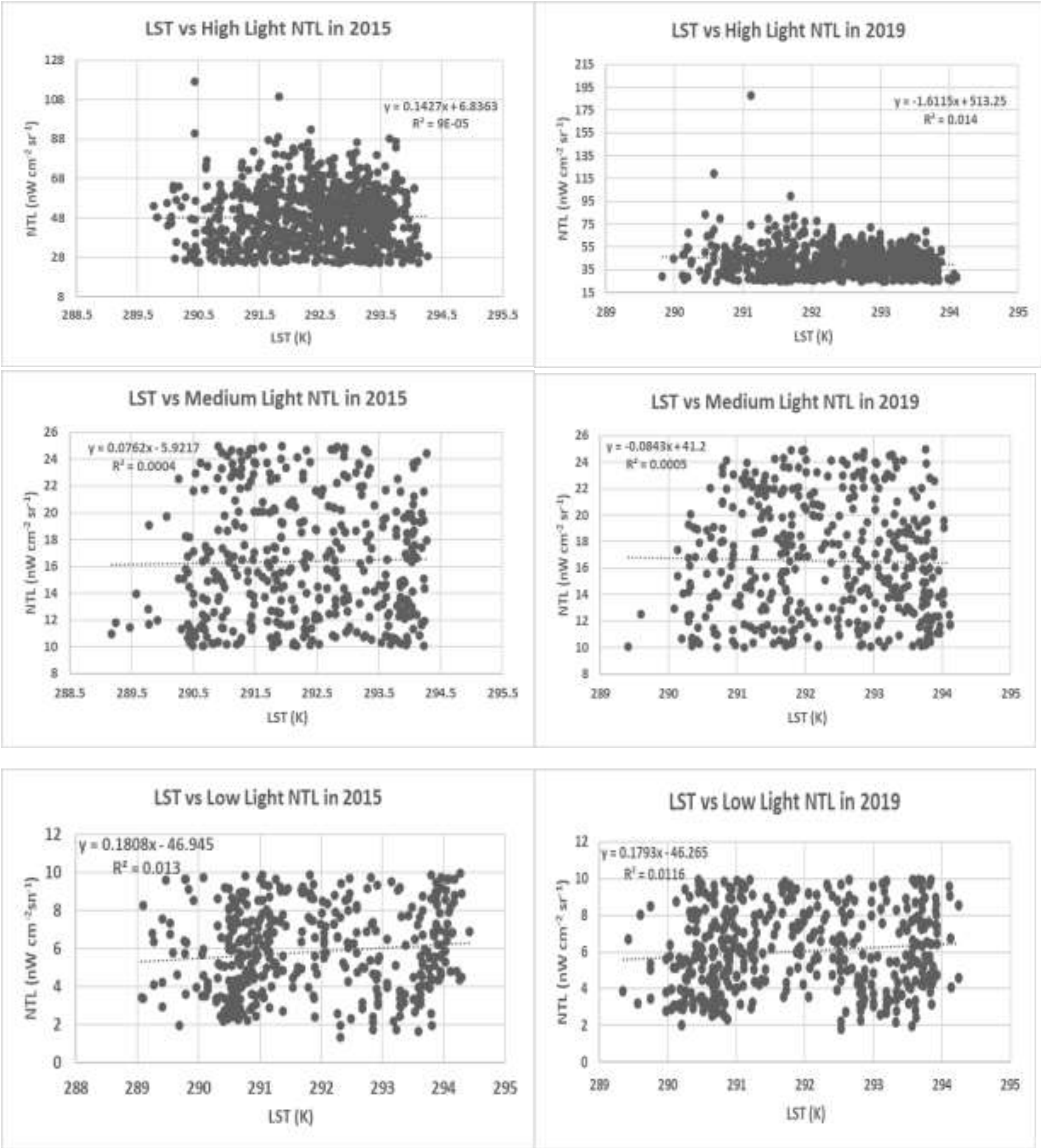

Fig.6 Scatterplot between LST and NTL for the intensity of light

Table.3 Slope of LST-NTL and NDVI-NTL from the scatterplot

	2015		2019	
	LST vs NTL	NDVI vs NTL	LST vs NTL	NDVI vs NTL
Settlements	1.99	72.32	0.95	57.08
Cropland	13.86	132.74	7.84	74.06
Other Classes	12.75	78.38	12.61	121.65
Low Light NTL	0.18	1.09	0.18	1.77
Medium Light NTL	0.08	4.75	-0.08	3.94
High Light NTL	0.14	21.98	-1.61	22.54

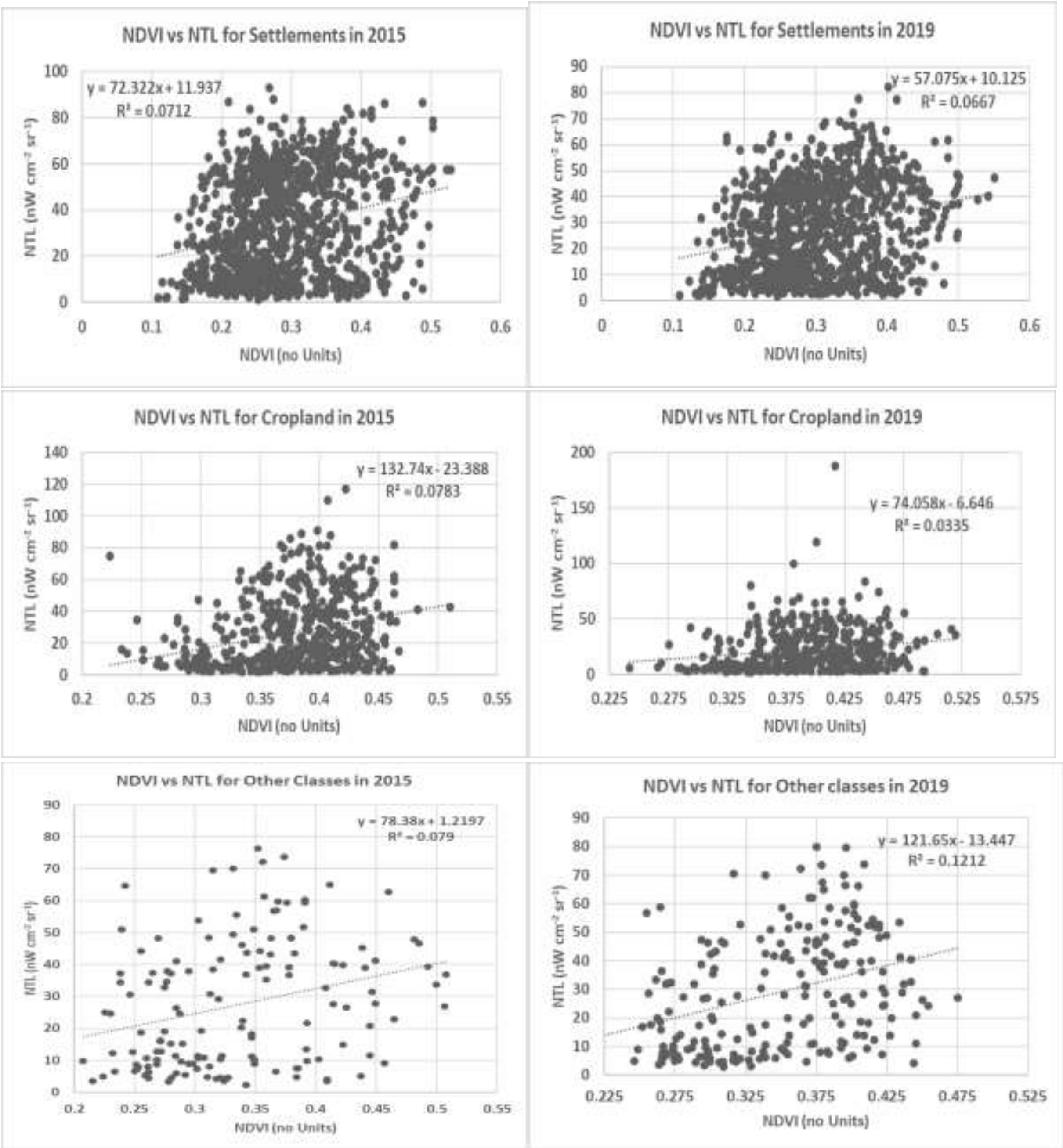

Fig.5 Scatterplot between NDVI-NTL for land cover type

Table.4 R^2 from the scatterplots

	2015		2019	
	LST vs NTL	NDVI vs NTL	LST vs NTL	NDVI vs NTL
Settlements	0.01	0.07	0.00	0.07
Cropland	0.21	0.08	0.07	0.03
Other Classes	0.22	0.08	0.16	0.12
Low Light NTL	0.01	0.00	0.01	0.00
Medium Light NTL	0.00	0.01	0.00	0.00
High Light NTL	0.00	0.01	0.01	0.02

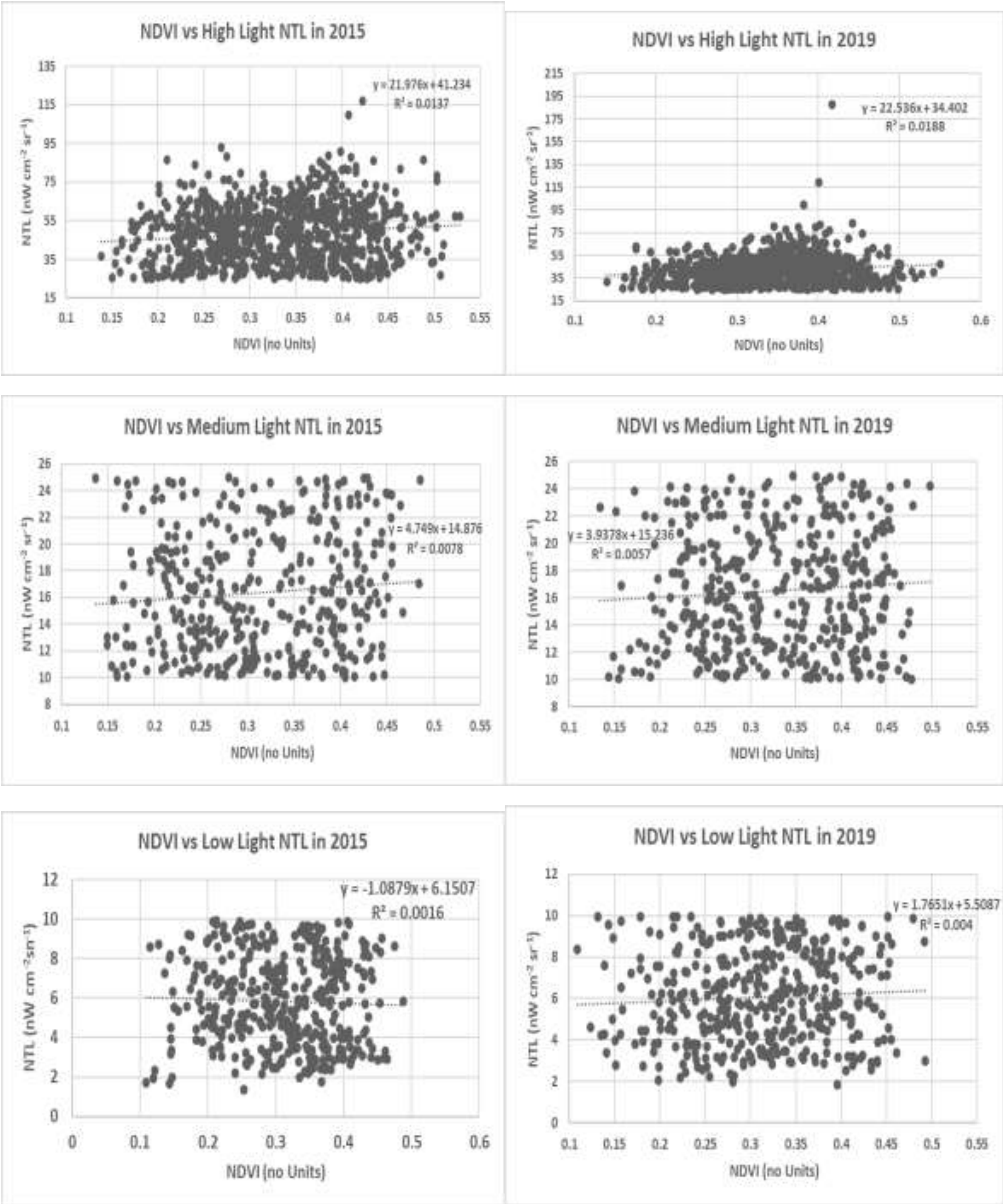

Fig.6 Scatterplot between NDVI and NTL for the intensity of light

Table.5 Results of the Pearson correlation coefficient (*R*)

	2015		2019	
	LST-NTL	NDVI-NTL	LST-NTL	NDVI-NTL
Settlements	-0.16	0.27	-0.04	0.26
Croplands	0.18	0.28	0.26	0.18
Other Classes	0.20	0.28	0.40	0.35
Low Light	0.02	-0.03	0.10	-0.01
Medium Light	-0.05	0.09	0.04	0.08
High Light	-0.01	0.12	-0.11	0.14

Table 3 shows the slope of the linear regression line, the slope indicates the change of dependent variable corresponding to the change in the independent variable, thus the change in NDVI and nighttime LST over the different land cover classes and light intensity levels have a significantly very less impact on the changes in NTL.

Table 4 shows the R^2 from the linear regression of the scatterplots. It measures the proportion of variation in the NTL (which is a dependent variable) in accordance with the change in LST and NDVI in 2015 and 2019. The positive direction of R^2 between the NDVI and NTL shows that when the NDVI (vegetation) value increases the NTL intensity tends to decrease and when the NDVI decreases the intensity of NTL increases. The positive direction of R^2 value of LST-NTL from 2015 and 2019 shows the NTL intensity tends to increase when LST increases and while for the negative direction of R^2 shows that NTL tends to decrease when the nighttime LST increases.

Table 5 shows the Pearson correlation coefficient between LST-NTL and NDVI-NTL for 2015 and 2019, the negative value of coefficient between LST and NTL show indicates that when the LST increase the NTL decrease which is observed in settlements of land cover type while positive correlation coefficient value along the croplands and other classes shows the NTL tends to increase when the LST increases, which is in a positive direction from 2015 and 2019. The correlation coefficient value of LST and NTL for the night light intensities shows a negative direction along with the high light areas (the NTL decreases when the LST value increases), while there was a positive direction of correlation coefficient along medium and low light areas form 2015 and 2019. The positive correlation coefficient value for NDVI and NTL shows that the NTL tends to decrease when the NDVI increases which were observed along with the land cover types for 2015 and 2019. While there was a negative correlation coefficient value between NDVI and NTL for high, medium, and low light intensities.

6. Discussion:

The Pearson correlation for the LST and NTL at different land cover classes and the nighttime levels shows the relationship between the LST and NTL in 2015 and 2019 (Table.5). Based on the correlation coefficient (R), the relationship between the LST and NTL for the medium light in 2015, high light in 2015 and 2019 show a weak negative correlation between the variables for low light and medium light. There is an increase in the correlation coefficient value of LST and NTL for the different land cover classes when compared with 2015 and 2019. Though the R value is less it shows an upward trend significance for all the classes in both the period, thus the considerable increase in the significance of LST and NTL in other land cover classes. The weak negative value in the settlements class shows the increase in R value in 2019.

From the results of the correlation coefficient of the Pearson method, it shows a weak negative correlation between the NDVI and NTL for low light in 2015 and 2019. The relationship between NDVI and NTL on each level of light intensity shows the trend of increase in the R value throughout the study period, which is considerably low. The R value of other classes has increased while it is decreasing in the settlements and croplands.

The R^2 from the scatterplot varies from 0 to 1, from Table.4 it shows that the LST of croplands in 2015 can explain the 20.8% NTL changes and 21.91% of other classes. Thus, the R^2 values for the different classes of land cover and light intensity are low which is not significant which are not sufficient to establish the relationship between the NTL and LST.

The negative correlation coefficient value between the NDVI and NTL shows that there is a negative relationship between the vegetations and build-up areas. The correlation between the NDVI and NTL might be high among certain areas in the study due to the high absorption of the lights by the vegetations along with the considerable high surface area of the vegetations (Levin & Duke, 2012)

Thus, based on the partition of the intensity of the lights classified above in this method, the relationship between LST and NTL is not achieved as it shows an irregular pattern of correlation which is weak. While The correlation between the LST and NTL is significantly high among the parcel level and mean LST at each NTL intensity level (Chen, et al., 2017).

7. Conclusion:

In this study, the data of NTL, LST, and NDVI were used to analyze the relationship between the NTL-LST and NTL-NDVI for different classes over the region of New Delhi, the relationship between the variables are found to be weak and statistically not significant. The study has been carried out only for the region of Delhi which exhibits an irregular pattern of the surface temperature and2 the NTL, the analysis was based on the pixel level intensity of the NTL, LST, and NDVI. Thus, there is significantly less relationship between the LST at nighttime with the NTL.

Answer to research questions:

- Does the LST influence on NTL over the urban area?

Using the pixel level correlation of LST and NTL in this study, it has been observed that there is significantly no correlation between the LST and NTL over the urban areas (settlements), while it shows a weak positive correlation for the croplands and the other classes (which includes wetlands and water bodies) in 2015.

- What are the significant factors that influence the NTL?

From the results of Pearson correlation and scatterplot, neither of the factors considered in the studies shows a significant correlation with the NTL using this methodology and the datasets.

Future scope:

Based on the data and methodologies applied in this study, the LST and NDVI have a weak correlation with NTL, thus the analysis can be performed with the other factors such as population density and POI, to find the influencing factor of NTL. The higher spatial resolution data at a parcel level analysis of data produces better correlation results in the relationship between LST and NTL. The drastically high DN values of pixels in urban centres that occurs due to high intensity of lights which hinders the calculation should be removed in the NTL. It is therefore recommended to apply the techniques on higher spatial resolution dataset such as NTL from Luojia, LST from Landsat nighttime and NDVI from Landsat. The current study area there is ambiguity in satellite derived land cover and actual land use, which could have hampered the relationships being searched for.

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