Detecting Relationship between Night Time Light (NTL) Data and Normalized Difference Vegetation Index (NDVI) values in Khoms city, Libya

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Abstract

This is an environmental study to show the spatial and temporal relationship between the optical density of population growth and decrease in vegetation cover in Al-Khums city, Libya. Relative to vegetation density, Landsat-8 satellite images were used and were extremely useful in understanding the temporal and spatial change of vegetation (NDVI) accurately by selecting cloud free images. Comparing the relationship between them using linear analysis showed that the

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relationship was negative during the study period, and the discrepancy between the areas of light density (population density) and distribution of vegetation was clear, noting that soil erosion and lack of vegetation can also be the result of overgrazing or open quarries in the study area.

Keywords: *NDVI, NTL, DMSP / OLS,Khoms city, Libya.*

1. Introduction

The DMSP sensor was launched in 1965 for NTL observations. The resolution of the space component is 2.8 km, the world observations are in 14 orbits daily. The NTL sensor has been installed in the DMSP since 1976 for observing the clouds, the light sensitivity of the night recorded in table 1 by night satellite were from the classified military classification in 1972, Night data was available and accurate (Meng, et al.2014).

Electrical energy is a part of energy consumption, Military Meteorological Satellite, DMSP(Defense Meteorological Satellite Program) installed with Program to understand as a distribution of the light of the evening on the earth by NASA. Light distribution depends on nature, such as aurora, many are in the city, the slash-and-burn field, the gas of the oilfield zone it is light from human activities such as burning and fishing. Among them, city lights include interior lights of office buildings, transportation networks, streetlights, includes light emitted from houses, etc. It is due to electricity consumption. According to Alexander, et al (2010), the tendency of the light distribution is closely related to the human activities of the area, and the light distribution was estimated as indicate to population grow at the local level. According to statistical data of each country, DMSP / OLS Satellite can grasp the surface light distribution(Kiran, et al.2009).

The used data were an effective means. To obtain energy from this nighttime light (NTL) data, NDVI data is an effective means for an illustration of the population growth supported by Nighttime light (NTL) data over several years, the amount of energy from the DN (Digital Number) value is 6 bits. and when the light energy has a certain value If it exceeds, the data will be confused. In addition, when the NDVI coefficient is troubled through many years, the light intensity values are difficult to analyzing. For these problems, Doll,et al (2006) used NTL data of multiple scenes by intensity of light. NTL data is characterized by its output level is 6 bits (0 to 63 range), where the energy of light not exceeds of the certain value. In other words, the NTL value is very saturated at 63 (Letu, et al.2010).

Also, NTL values changing according to strength . According to Table 1, there is a strong relation between orbit width and time, where little time in low orbit. Therefore, for each time, these changes to orbits width lead to changes in NTL intensity saturation. It is necessary to understand the mechanism of remote light intensity sensing. Regions where the sensing level of NTL data is high, the intensity of light saturation at night is obvious(Elvidge, 1999).

According to Elvidge (2007), to estimate the light at night, among the data observed during the 15 days from recorded by DMSP, and if clouds influence is 90% or more it is removing the scene of the data. Next, for all DMSP scenes calculate the frequency distribution of the data of the scenes of which light was confirmed then remove data whose frequency distribution is 10% or less. The observation for each scene to estimate the light intensity distribution by calculating the energy value.(He, et al.2014), DMSP data for one year noise is removed from the NTL value ranges from 0 to 63 not from 0 to 100 or 99 .

Table 1 Characteristics of DMSP/NTL data

Orbit	Polar Orbit
Altitude	Perigee altitude 843km Apogee altitude 854km
Inclination	98.9°
Period	101.8 minutes
Objective	Cloud distribution
Wavelength	Visible and Near-IR) day（0.4－1.1µm
	Visible and Near-IR) night（0.47－0.95µm
Swath width	3000km

Source: National Geophysical Data Center) NGDC, 2011（.

This calibration data makes it possible to relate NTL digital numbers back to the laboratory observed radiances known in terms of W/cm^2/sr/m. The solid diagonal line indicates the saturation radiance (digital number 63dB). Observed dB pixels with radiances greater than this radiance yield digital number values of 63. The dashed diagonal line indicates the dB radiance for a digital number of 1(Elvidge,2007).

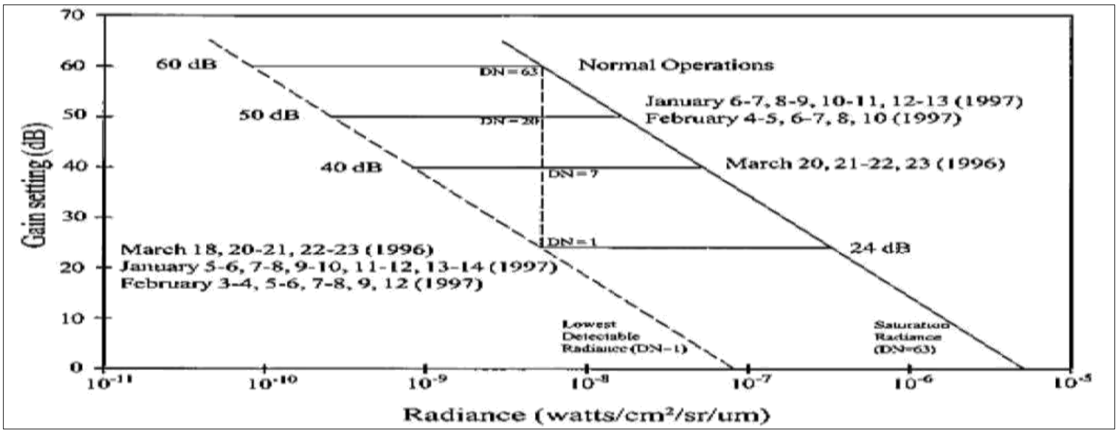

Figure .1 Shows the relationship between the DMSP and dB (dB is the log of the amplification).radiances based on the preflight sensor calibration(Elvidge,1999**).**

DMSP aims to bring together all data, all software/tools/libraries, and all documentation needed by the users to analyze or process NTL data on one single platform with scalable Information and Communication Technology (ICT) resources . With DMSP can view the NTL data in full resolution. NTL data between 300 m and 100 m detect the derived vegetation parameters from the Copernicus Global Land Service(Elvidge,**1999**).

2.Methodology

2.1 Study area covered;

Khoms city (Figure 2) located in Northwest of Libya, the area of city is about 151.90 km^2(94.39^2 mi), and the metropolitan areas , also land uses, as shown in Table (2). It is characterized by the abundance of olive, palm, pine, cypress, and optimum trees, vineyards, citrus, almonds, carobs, thyme bushes, wormwood grasses, castor and carob trees. Also, agricultural crops such as barley, alfalfa, and many seasonal fruits. And the pastoral areas are prevail.

Figure 2. Study area of Khoms city

Table 2 Classification of vegetation during study area

No	Classification	Area(hectare)	%
1	Urban land	2120.3	2.4
4	Irrigated cropland	4485.9	0.5
5	Rain fed agriculture lands	14489.6	16.1
7	Forests and shrubs	4624.9	5.2
8	Pasture lands	55439.6	61.8
9	Barren territory	8608.5	9.6

Source (Al-Alem, et al.2017)

2.2 Light intensity distribution estimation method;

The ELL method proposed in this research for land cover classification, and residential areas by light-emitting. It corresponds to the analysis range of light intensity to NTL data, each pixel value range was 1 km × 1 km. The calculation is shown in equation (1) (Zihao,et al.2019):

$$La) = U_1 \times a + U_2 \times b + R_1 \times c + R_2 \times d + F \times e \ (/Np$$

Where;

La: occupied area ratio of light emitting artificial coated area

U_1: Area of the densely built urban area (m^2)

U_2: Area of the city area (m^2)

R_1: Area of dense residential area (m^2)

R_2: Area of residential area (m^2)

F: Area of the factory (m^2)

Np: area of one pixel of NTL data (m^2)

a ∼ e: corresponding to each land covering item ccoefficient of weight of light quantity.

In equation (1), In each area of the light-emitting area, Illuminance was measured on the ground using an illuminometer. And based on the measurement result. NTL data weighted for estimating NDVI. Next, using NTL data, light intensity saturated from the light-emitting compare to same area of land cover classification data. Based on the regression equation between measured area ratios and light (Huang,et al.2014).

2.3 NDVI data;

NDVI techniques used for extracting the various features presented to three bands of Landsat-8 satellite images to Khuoms city. Vegetation cover is one of the most important biophysical indicators of soil erosion, which can be estimated using vegetation indices derived from the satellite images. Vegetation indices allow us to delineate the distribution of vegetation and soil based on the characteristic reflectance patterns of green vegetation. The NDVI is a simple numerical indicator that can be used to analyze the remote sensing measurements, from a remote platform and assess whether the target or object being observed contains live green vegetation or not. From equation (1) and equation (2) (Karnieli, et al.2010).

,NDVI is calculated as follows:

RNDVI= $\frac{NIR - RED}{NIR + RED}$,where (0<NDVI>1)……………….(1)

GNDVI= $\frac{NIR - GREEN}{NIR + GREEN}$where (0<NDVI>1)………………(2)

Where RED is a visible red reflectance, and NIR is near-infrared reflectance. The wavelength range of NIR band is (750-1300 nm), Red band is (600-700 nm), and the green band is (550 nm). The NDVI is motivated by the observation vegetation, which is the difference between the NIR and red band; it should be larger for greater greenness density. It takes the (NIR - red) difference and normalizes it to balance out the effects of uneven illumination such as shadows of clouds or hills (Gamon, et al.2015). In other words, on a pixel by pixel basis subtracts the value of the red band from the value of NIR band and divides by their sum. The very low value of NDVI (0.1 and below) corresponds to barren areas of rock and sand. Moderate values represent shrub and grassland (0.2 to 0.5), while high values indicate temperate and tropical rain forests(0.6 to 0.8). Bare soil is represented with NDVI values, which are closest to 0 and water bodies are represented with negative NDVI values. (Xie, et al,.2010).

2.4 Research method;

The NTL data corrected geometrically using the ETM data projected to the ELL method. The NTL values are compared by time series evaluation. Estimation of the saturated digital number (NTL) value to the scope of the observation scene is limited in the clear sky only. Then, a light intensity NTL value estimation image is created by comparing the NTL value that not saturated and that saturated value. estimating the saturated NTL value of the sentinel-2A satellite for the possibility of estimating the light intensity distribution during the summer season and late spring and early autumn. Comparative analysis between NDVI and NTL to evaluate whether the saturated value of the estimated DMSP data is valid. Study areas including each target location from Khoms city out of the acquired NTL data is projected and converted to a conform cone projection method. Classification items were clouds free.

using visible color, vegetation is segmented , distinguishing between urban areas and residential areas for more accurate.

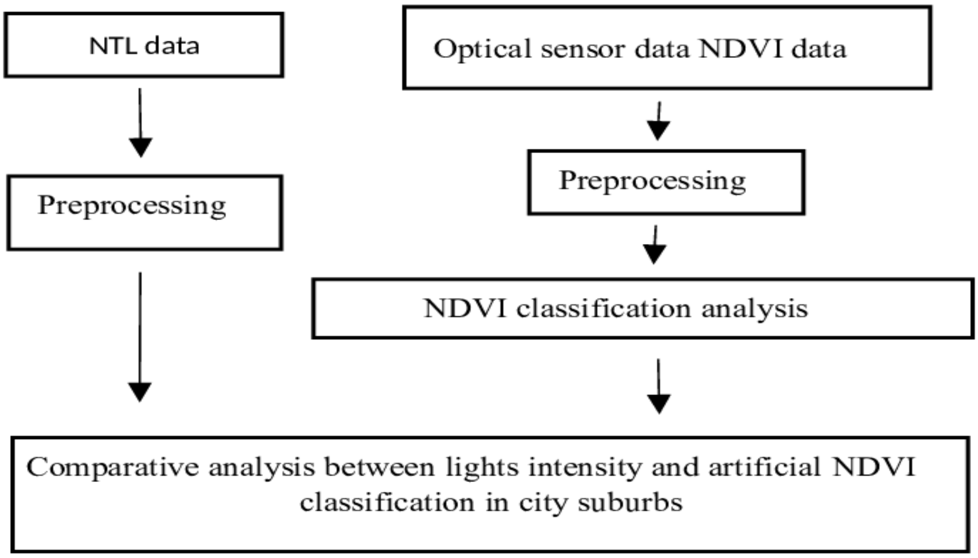

Figure 3. Research approach

After classification accuracy of NTL and NDVI data of all items exceeded 70%, land cover classification processing by maximum likelihood method was carried out. Where the classification accuracy of the densely urban area, because of the dense urban area are complicatedly included within one pixel. For the classification data, the values were compared between the pixels of the estimated light intensity (NTL) value estimated from the land cover color image of NDVI data .

3.Results and discussion:

In this study, three types of land cover in the study area were extracted and classified using remote sensing and its high-resolution imagery. Figure 4 shows the result of urban vegetation mapping with NDVI threshold approach where green indicates high vegetation, yellow for low vegetation and brown for non-vegetation area. The NDVI threshold value able to identify the vegetation types in urban area. For example, the NDVI value threshold from 0.501 to 1.0 indicate the high vegetation like trees in urban areas, while lower value represents low vegetation and non-vegetation. With the use of Landsat-8 data the vegetation classification can be mapped accurately. The classification result is based on NDVI threshold value to classify non-vegetation (-0.12 to 0.19), low vegetation (0. 2to 0.5) and high vegetation (0.501 to 0.78). The regression analysis used to classify the vegetation types in the study area. From the classification result, the accuracy reflected the effectiveness of classification methods for urban vegetation mapping. NDVI data collection were referred to validate the vegetation types from the classification process. Thus, reliable result achieved and vegetation in urban area was mapped accurately.

Figure (5) shows the night NTL images of the study area. Satellite images different in the distribution of light intensity over the study area. NTL value (light intensity) was illustrated by using Pancometric reflection to demonstrate more than the spectral distribution of light colors. NTL data can be easily converted to an energy value by an exponential function between the estimated NTL value and the light energy value using the ELI method(Elvidge, 2009; Kohiyama, 2014).

NTL classification result is based on light energy value to classify non-light (0 to 10), low light (11 to 20) and high light (0.21 to 0.63).

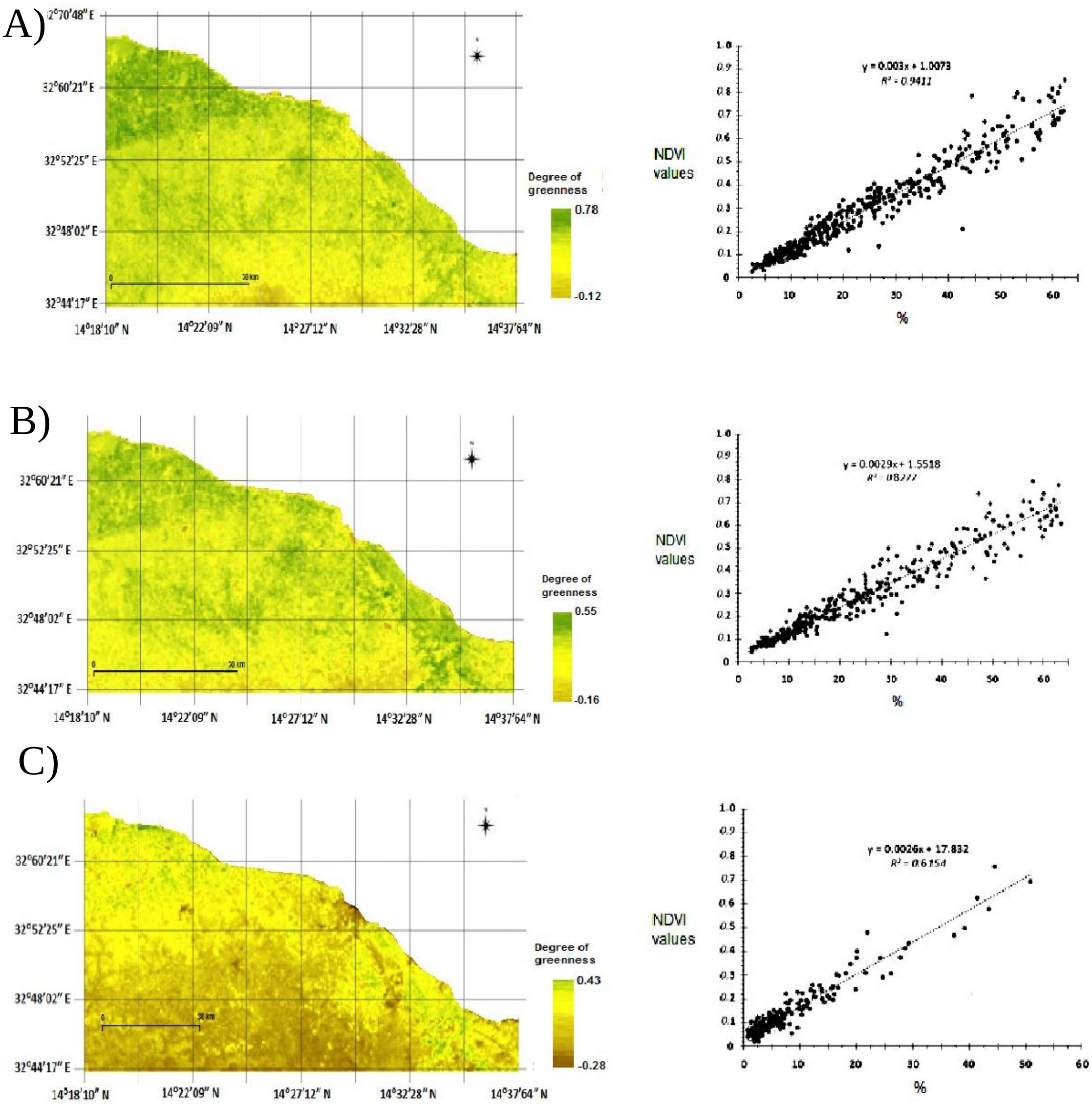

Figure 4 . Prevailing patterns of NDVI values during study period and their regression lines, where section (A) from 1993 to 2000,section (B) from 2001 to 2010, and section (C) from 2011 to 2018.

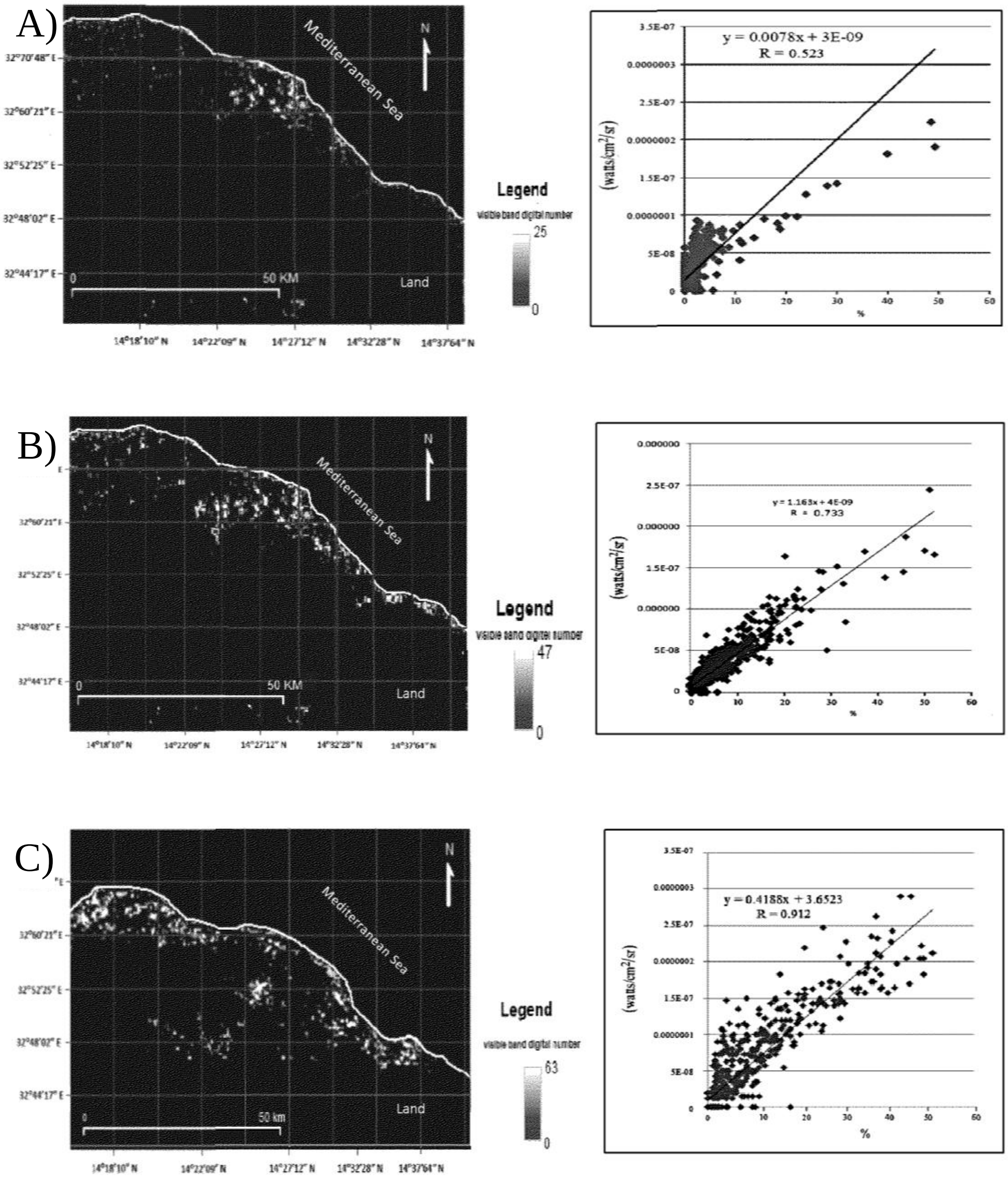

Figure.5 NTL observations during study period, where section (A)from 1993 to 2000,section (B) from 2001 to 2010, and section (C) from 2011 to 2018.

Relationship between NDVI values and DMSP- NTL data were low(Figure 6), the correlation coefficients between the light distributions and NDVI values of the NTL data were respectively, r^2=0.332 in section (A), r^2=0.285 in section (B), and r^2=0.236 in section (C). Where the colors mean the difference in the similarity rate between NDVI and NTL average values, it ranged from red color, which represent high values to light blue color ,it indicates to low values. According to these light intensity, NTL values were, the highest in city center, where the light intensity decreases gradually from the suburbs . DMSP values not similar to NDVI data. The validity estimation by the ELL method was evaluated by comparison between different sites in the study area.

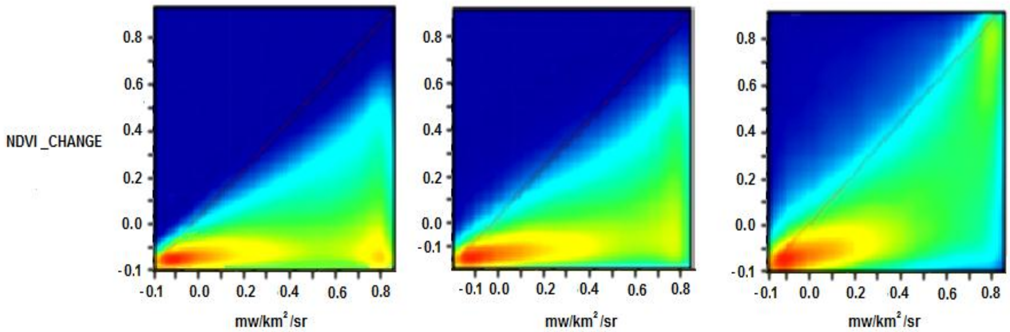

Fig.6 The correlation coefficient between the NDVI values and DMSP-NTL values using ELL method was counterproductive and weak.

The investigation results of the study area were summarized as follows:

1) It was difficult to observe the building lights accurately
2) Decrease in vegetation cover was the best measure of population increase in the study area.
3) The NTL values for the city center were a maximum of 190.3 lux.
4) The weakest NTL value for luminaires was 7.28 lux appearing in the southeast part of the city

5) The highest value of the vegetation index recorded 0.43, which indicates to weak of the vegetation in the study area.

5. Conclusion:

ELL method proposed recently with ground cover information for estimating the value of DMSP-NTL in urban region data by the light intensity value, and the NDVI data were analyzed based on the vegetation cover classification data. Some important notes were summarized in this study:

1) There was a weak correlation between light emissions (NTL) and NDVI data expressed by the linear regression.
2)An inverse relationship has increased in the last decade of study years.
3) The possibility of applying the ELL method to estimate the distribution of light intensity in the study area.
4) The light intensity saturation range of Landsat-8 technologies is affected by clouds and heavy rains.
5) Need to more environmental studies, that specialized in close sensing, such as aerial surveys and ground sensors for more accurate to the population distribution.

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