Assessment the Relationship between LST and Built-Up Area Utilizing Landsat Images in Al Diwaniyah Governorate

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Abstract:

In many large cities, the built-up area shows remarkable growth during the last decades. Land surface temperature is an important factor in climate change and vegetation growth and many land surface processes. This study aims to assess the relationship between land surface temperature (LST) and built-up area using Landsat 8 images in Al Diwaniyah governorate for the years 2014 and 2018. Normalized Difference Built-up Index (NDBI) has been used to extract the built-up area from Landsat 8 images using ArcGIS 10.5 software. The result showed a linear correlation between increasing the built-up area and the higher LST values, which mean that there was a positive relationship between the normalized difference built-up index values and LST. The results show that the increase in the built-up area leads to increasing the LST in the urban area directly.

Keyword: Built-Up; Remote sensing; LST; GIS; NDBI.

تقييم العلاقة بين درجة حرارة سطح الأرض والمناطق المبنية باستخدام صور لاندسات ٨ في محافظة الديوانية

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الخلاصة:

في العديد من المدن الكبيرة، شهدت المناطق المبنية نموا ملحوظا خلال العقود الماضية. اذ تعد درجة حرارة سطح الأرض عامل مهم في دراسة التغيرات المناخية والنباتات والعديد من دراسات سطح الأرض. تهدف هذه الدراسة إلى تقييم العلاقة بين درجة حرارة سطح الأرض والمساحة المبنية باستخدام صور لاندسات ٨ في محافظة الديوانية للأعوام ٢٠١٤ و٢٠١٨. تم استخدام مؤشر الفرق الطبيعي للمناطق المبنية لاستخراج المساحة المبنية من صور لاندسات ٨ باستخدام برنامج ArcGIS 10.5. أظهرت النتيجة وجود علاقة خطية بين زيادة المساحة المبنية وقيم الحرارة السطحية الأعلى ، مما يعني أن هناك علاقة إيجابية بين قيم مؤشر الفرق الطبيعي للمناطق المبنية وقيمة حرارة سطح الأرض. يوضح هذا البحث أن الزيادة في المساحة المبنية تؤدي إلى زيادة درجة حرارة سطح الارض في المناطق الحضرية بشكل مباشر.

الكلمة المفتاحية: المناطق المبنية، التحسس النائي، درجة الحرارة السطحية، نظم المعلومات الجغرافية، مؤشر فرق المناطق المبنية.

1. Introduction

Nowadays, many developing countries are suffering from rapid urbanization, which can endanger the sustainable development of urban areas (Wu et al., 2014). According to the United Nations (2015) by 2050, about 66% of the population in the world will live in urban areas. At the same time, as more than half the world's population lives in urban areas, cities are highly vulnerable to climate change, because they focus not only on people but also on assets and infrastructure (De Gregorio et al, 2015). As a result, there have been dramatic changes occurred in urban areas. Also, the effect of city expansion has altered the local climate. Accordingly, one of the major issues of climate change in urban areas is the increase in surface temperature. For example, IPCC (2014) predicted an increase in the global surface temperature over the 21st century. The effects of this phenomenon could lead to periods of heat waves, which will affect in particular urban population around the world.

Land surface temperature (LST) plays a vital role in many land cover processes and environmental studies (Quattrochi and Luvall, 2004). Generally, the LST used to estimate the temperature spatial distribution change, that considers being a major climate parameter, related to surface energy balance (Xiao *et al.,* 2007). LST means "the surface temperature that observed if directly contact or touch it with, also refer as the skin temperature of the surface". Assessing the LST is very important in different analysis and environment problems (Orhan et al. 2014).LST could be calculated from remotely sensed data that may be used in environmental applications such as urban planning, agriculture, climate change, and hydrology. LST is related to the transport of heat between the land surface and the atmospheric boundary layer (Jia et al., 2001). Energy absorption and emission by atmospheric water vapor, clouds, and greenhouse gases affect radiative balance. The increased concentrations of some of these gases, such as CO_2, contribute to climate change. Continuous LST monitoring on a global scale is necessary for characterization of such changes in climate and explains an increased interest in operational LST estimation. A specific problem in urban areas is the increase in the temperature; this is because of the conversion of vegetation-covered area to asphalt roads, residential, commercial and industrial areas (Weng et al., 2004).

Remote sensing data are suitable for understanding the change in land cover relative to basic physical properties in terms of surface radiation and emissivity. Currently, many satellites provide data with global coverage on the thermal band of the spectrum in various spatial and temporal resolutions. For example, the Landsat satellite provided global imagery since 1984. Landsat 8 launched in 2013 giving continuity to the data record, Landsat 8 captures the temperature of the Earth's surface in two bands (band10 and band11) with 100m spatial resolution. Estimate the surface emissivity from satellite data is available in Li et al. (Li, et al., 2013). Normally, the

LST increases prior to a decrease in the plant cover (McVicar, et al., 1998). Many methods were proposed to estimate the emissivity based on NDVI, this is because of the high correlation between NDVI and surface emissivity (Olioso, 1995; Van de Griend and Owe, 1993).

This study aims to evaluate the relationship between LST and the built-up area in Al Diwaniyah governorate utilizing Landsat 8 images for the years 2014 and 2018.

2. Methodology

2.1 Study area

Al-Diwaniyah (previously Al-Qadisiyah) is one of the governorates of the Middle Euphrates region, within the area of the Iraqi flood plain, which generally has a slight slope from the northwest to the south and southeast and a branch of the Euphrates River, known as the Shatt al-Hilla, passes through the governorate. It is located between longitudes 8 317 and 21 327 North and latitudes 25 447 and 45 45 East (Figure 1). As for its administrative borders, it is bordered to the north by Babel and Wasit governorates, to the east by Dhi Qar and Wasit governorates, to the south by Al-Muthanna and to the west by Najaf governorate. The area of Al-Diwaniyah governorate is about 8153 km2, thus it constitutes about 1.9% of the total area of the country, and the population of the governorate is estimated at 1.5 million according to the 2014 census. The governorate currently has four districts: Al-Diwaniyah district (governorate center), Afak, Al-Shamiyah, and Al-Hamzah. The governorate includes shrines of a number of Islamic holy figures, as well as traces of the oldest civilizations in the ancient world, including the ruins of the city of Nefer, which was called "Nibor" on the outskirts of the city of Afak, 25 km from the governorate center. As well as Warka city (Ancient Uruk), one of the most important cities of the Sumerians in the fourth millennium BC.

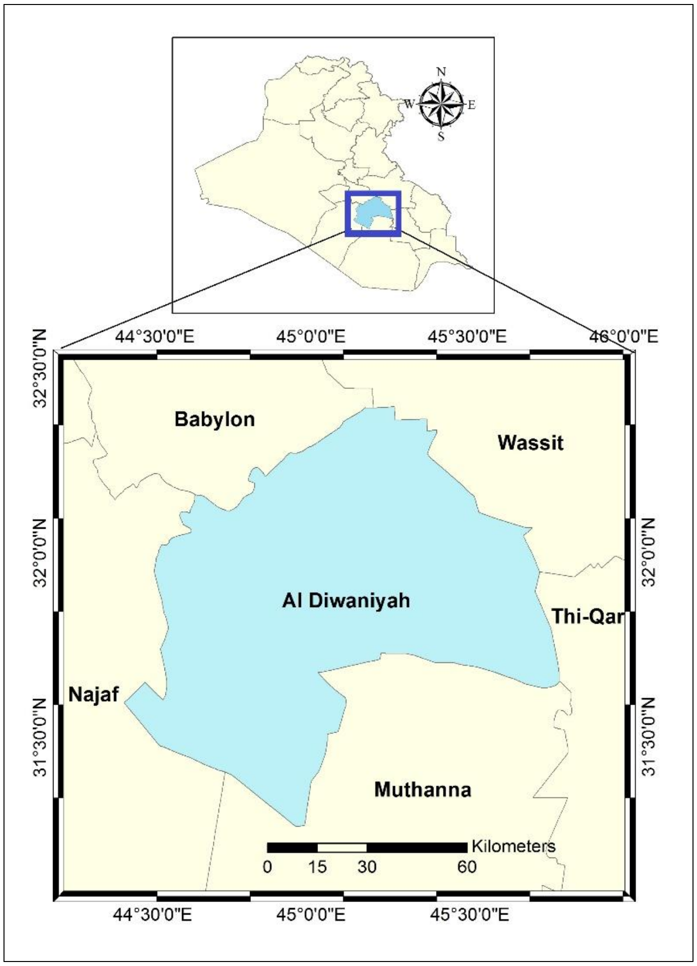

Figure 1: Location of the study area.

2.2 Dataset

Beginning with the first mission in 1972 Landsat satellites have been monitoring Earth environment building up regularly updated global archive. Due to their spatial (Optical: 30 m, and thermal 60-120 m), spectral (7 or more bands including 1 or 2 thermal infrared) and temporal (16 days revisiting period) resolution Landsat images are the most widely used source of remote sensing data (Miller et al., 2013). In this study, Landsat 8 multispectral images were used to generate LST, NDVI and NDBI maps, the image specification illustrated in Table 1. Cloud-free images downloaded for month March 2014 and 2018.

Table 1: Landsat 8 images specification.

Path/Row	Dates	Time	Sun-	Sun-	Datum

			azimuth	elevation	
167-38	2014/3/16	07:28:04	141.373	49.573	WGS84/UTMZone38
168-38	2014/3/23	07:34:07	139.652	52.165	WGS84/ UTMZone38
167-38	2018/3/11	07:27:10	142.260	47.630	WGS84/ UTMZone38
168-38	2018/3/2	07:33:27	144.204	44.372	WGS84/ UTMZone38

2.3 Satellite data processing to estimate the LST

The approach to the proposed work to estimate LST using Landsat 8 data is shown in Figure 2, where band10 was used to estimate brightness temperature, whereas band4 and band5 were used to calculate the NDVI.

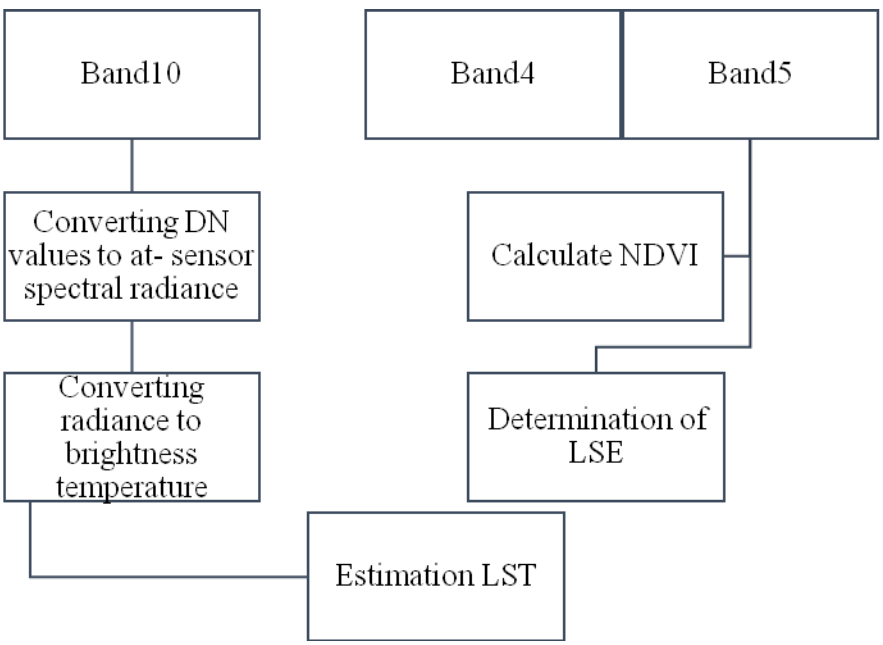

Figure 2: Methodology of this study using Landsat 8 data.

Step1: Convert the Digital Number (DN) to an absolute radiance supposed converting the pixel value of the thermal band(Band 10 for Landsat 8) in sensor spectral radiance (LS) using the equation (Walawender, et al., 2012; Kumar and Shekhar, 2015):

$$LS = gain * DN + bias$$

Where gain = 0.0003342; bias = 0.1.

Step 2: compute the sensor brightness temperature using Planck's Law to invert and calibrate the constants for sensor spectral radiance (Ls) transformation into sensor brightness temperature (Ts). "For Landsat 8 K1 = 774.8853, K2 = 1321.0789, ln =10.904" using the equation (Walawender, et al., 2012; Kumar and Shekhar, 2015):

$$Ts = \frac{K2}{\ln(\frac{K1}{Ls}+1)} \quad \dots (2)$$

Step 3: Calculate the NDVI, which is a numerical indicator which employs the Red band and near-infrared (NIR) band (For Landsat 8: Red=Band 4; NIR= Band 5) of the electromagnetic-spectrum (Ganie and Nusrath, 2016):

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad \dots (3)$$

Subsequently, NDVI values were transformed in LSE using "emissivity values": NDVI value ranging between −1 and +1, for soil 0.960, for vegetation 0.990, and for water 0.9950 (Walawender, et al., 2012).

Step 4: Estimated the LST using the Ls, Ts, and LSE. LST based on the formula (Walawender, et al., 2012):

$$LST = \gamma\left[\frac{1}{\varepsilon} + (\psi 1 Ls + \psi 2) + \psi 3\right] + \delta \quad \dots (4)$$

Where ε Land Surface Emissivity (LSE), LS is sensor spectral radiance, $\psi 1, \psi 2, \psi 3$ atmospheric functions calculated using the atmospheric parameters "atmospheric transmissivity, up-welling atmospheric radiance and down-welling atmospheric radiance" (IVAN, 2017).

2.4 Utilizing the NDBI to Estimate the built-up area

NDBI is used to extract built-up area; it was used firstly for Landsat TM data by Zha, et al in 2003. For Landsat 8 images, SWIR=B6, and NIR=B5.

$$NDBI = \frac{SWIR\,1 - NIR}{SWIR\,1 - NIR}$$

NDBI values the built-up area and barren pixels have a positive value which allowing the built-up area to be separated simply.

3. Results and Discussion

3.1 Land Surface Temperature results

LST maps were shown in Figure 3. For 2014, the computed minimum and maximum LST are 15.6 and 32.2 respectively. The result shows that the high temperatures were associated with the urban areas and barren soil, which range between 25 to 32.2 ºC, and the vegetation areas have temperatures ranging between about 15.6 to 20 ºC. The LST statistical data was shown in Table 2.

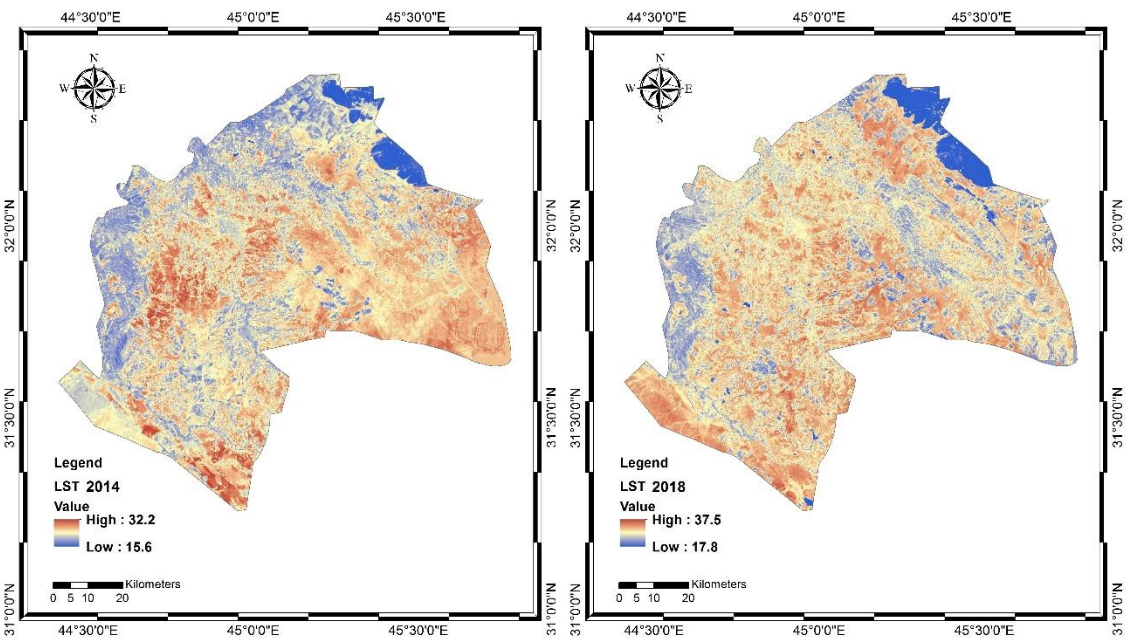

Figure 3: The LST results for the years 2014 and 2018.

Table 2: LST Statistical Data.

Year	Min.	Max.	Mean	St

	(C°)	**(C°)**	**(C°)**	**Deviation (SD)**
2014	15.6	32.2	24.3	2.5
2018	17.5	37.5	29.9	3.1

3.2 NDBI results

The NDBI results show that built-up areas in Al Diwaniyah governorate shown a slight growth during the study period (2014-2018). As shown in Figure the values of NDBI are higher in 2018 than in 2014 The NDBI maps are shown in Figure 4. The statistical data (Table 3) shown that the NDBI values are slightly increasing in the year 2018 than in 2014.

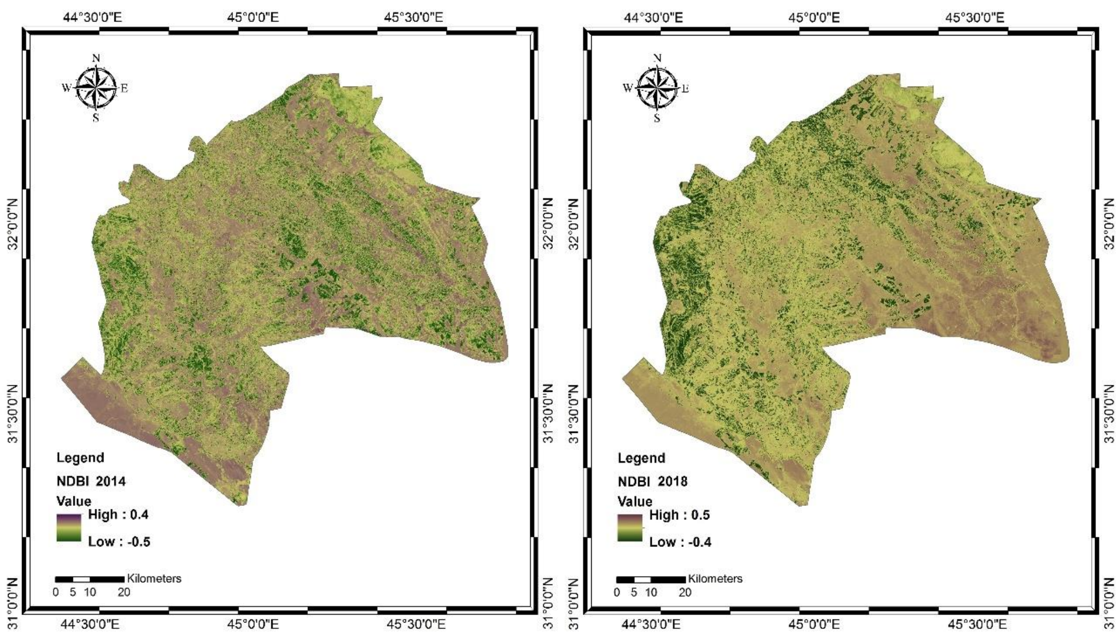

Figure 4: The NDBI results for the years 2014 and 2018.

Table 3: NDBI Statistical Data.

Year	**Min.**	**Max.**	**Mean**	**St Deviation**

				(SD)
2014	−0.5	0.4	−0.06	0.097
2018	−0.4	0.5	−0.03	0.092

3.3 NDVI results

NDVI data are shown in Figure 5 and Table 4. The NDVI values are higher in 2014 than in 2018. The results indicated that there was a linear correlation between the increase of the built-up area and the higher LST values while lower LST was associated with vegetation cover. Which mean that there was a positive relationship between the NDBI values and the LST values while the relation between NDVI and LST values was inverse.

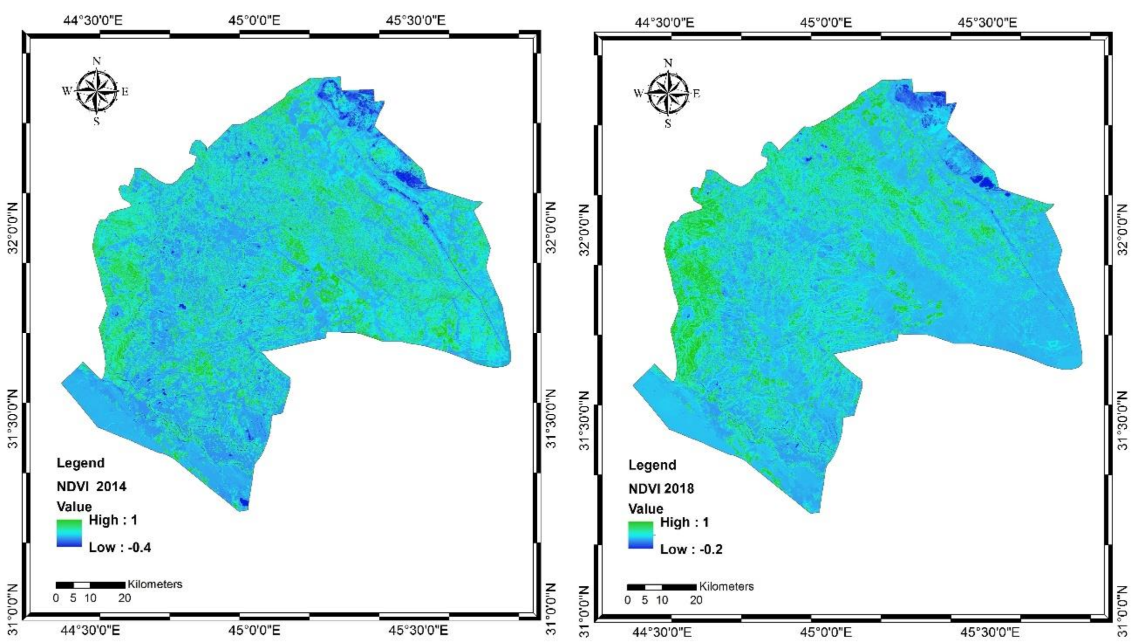

Figure 5: The NDVI results for the years 2014 and 2018.

Table 4: NDVI Statistical Data.

Year	Min.	Max.	Mean	St Deviation (SD)
2014	−0.4	1	−0.165	0.12

2018	−0.2	1	0.13	0.1

4. Conclusion

- In this study, Landsat images were used to estimate the LST changes between the years 2014 and 2018. The relationship between the built-up area and the vegetation cover were examined. During the study period, the built-up areas show slight growth in Al Diwaniyah governorate.
- The results indicate that there is a linear relationship between increasing the built-up area and the higher LST values whereas lower LST associated with the vegetation cover. Which mean that there was a positive relationship between the NDBI values and the LST while the relation between NDVI and LST was inverse.
- LST is considered as an important parameter. Modeling for estimating the LST from Landsat thermal imagery can be a good, time saving and effective options. In this study, the LST changes between 2014 and 2018 were estimated. For this period there was an increase of about 3 degrees. An analysis of LST maps reveals that minimum temperatures are found in vegetation cover, while maximum temperatures are in built-up areas.

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