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Remote Sensing - Based Analysis of LST and NDVI Correlation for the Coolest and Hottest Month of 2023 in Khanaqen City

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Abstract

Urban land cover characteristics often lead to variations in surface temperature. Remote Sensing (RS) and Geographic Information Systems (GIS) are valuable tools for obtaining detailed information about surface indices. This study evaluates the temporal variation of Land Surface Temperature (LST) in Khanaqen city, located in South eastern Iraqi Kurdistan and Eastern Iraq. The research investigates the relationship between LST and the Normalized Difference Vegetation Index (NDVI) for the coolest and hottest month of 2023 using Landsat images from the USGS Earth Explorer. The objective is to explore how green spaces influence LST during the cool, humid winter and hot, dry summer. Two satellite images from Landsat 9 were used to retrieve LST and NDVI for the study periods. The results indicate that green spaces significantly reduce LST in July, so that the result of the correlation analysis of variables, significant inverse correlation between LST and NDVI ($R = -0.53$, $R^2 = 0.28$ and P value = 0.00) highlights the effect of vegetation cooling. Conversely, January shows a modest correlation ($R = -0.01$, $R^2 = 0.00$, and P value = 0.90), indicating a minimal effect of vegetation cover on LST.

Keywords: Urban land cover, Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), green spaces, Remote Sensing.

1. Introduction

Urbanization and changes in land cover have a profound impact on local climate and environmental conditions (Grimmond, 2007). One of the most significant consequences is the variation in LST, which can influence urban heat islands, energy consumption, and overall urban sustainability (Zhang et al., 2017). Understanding the dynamics of LST is crucial for urban planning and environmental management, particularly in regions experiencing rapid urban growth and climatic changes (Shohan et al., 2024).

Changing vegetation cover significantly affects LST through several key mechanisms. Evapotranspiration, where plants release water vapour, cools the land surface by absorbing heat from the environment. A reduction in vegetation diminishes this cooling effect, raising LST, while an increase enhances it, lowering LST (Katul et al., 2012). Furthermore, trees and dense vegetation provide shade, significantly lowering the temperature of the ground beneath them. Loss of this shading effect results in higher surface temperatures, whereas expanding tree cover can mitigate this. Vegetated areas also possess different thermal properties than urban surfaces; soil and plants have higher heat capacity and different thermal conductivity, meaning they absorb and retain less heat. Changes in vegetation thus directly impact these thermal properties and LST (Lin & Lin, 2010). Additionally, urban areas with reduced vegetation often experience the Urban Heat Island effect, where temperatures are higher than in surrounding rural areas due to the concentration of heat-absorbing structures. Increasing urban vegetation can help mitigate this effect through cooling mechanisms like evapotranspiration and shading (Njoku & Tenenbaum, 2022). Overall, vegetation cover is crucial in regulating LST, with significant impacts from its increase or decrease.

Remote Sensing and Geographic Information Systems provide powerful tools for monitoring and analysing these environmental changes. By leveraging satellite imagery, researchers can assess various surface indices and their temporal variations with high accuracy and spatial resolution. Among the numerous indices available, the Normalized Difference Vegetation Index (NDVI) is widely used to measure and monitor vegetation health and density (Costa et al., 2020). The relationship between NDVI and LST is particularly important, as vegetation can significantly moderate surface temperature (Sun & Kafatos, 2007). As a study found that LST in the urban areas of the Lower Himalayan region has increased several folds due to land use\cover change in the past 30 years, this was primarily due to replacing vegetation by impervious surfaces (Ullah, et. all, 2023).

Previous studies have indicated the effect of vegetation cover on decreasing surface temperature, this study focuses on the correlation between LST and NDVI in Khanaqen city area. The study area situated in the south eastern part of the Iraqi Kurdistan region and eastern Iraq. The city experiences distinct climatic variations between hot, dry summer and cool, humid winter, these seasonal differences offer an ideal context to investigate the correlation between LST and NDVI for both season. By analysing data from the Landsat 9 (LC09) satellite imagery for coolest and hottest month of 2023, this research aims to quantify how green spaces influence LSTs across hottest and coolest month in the study area.

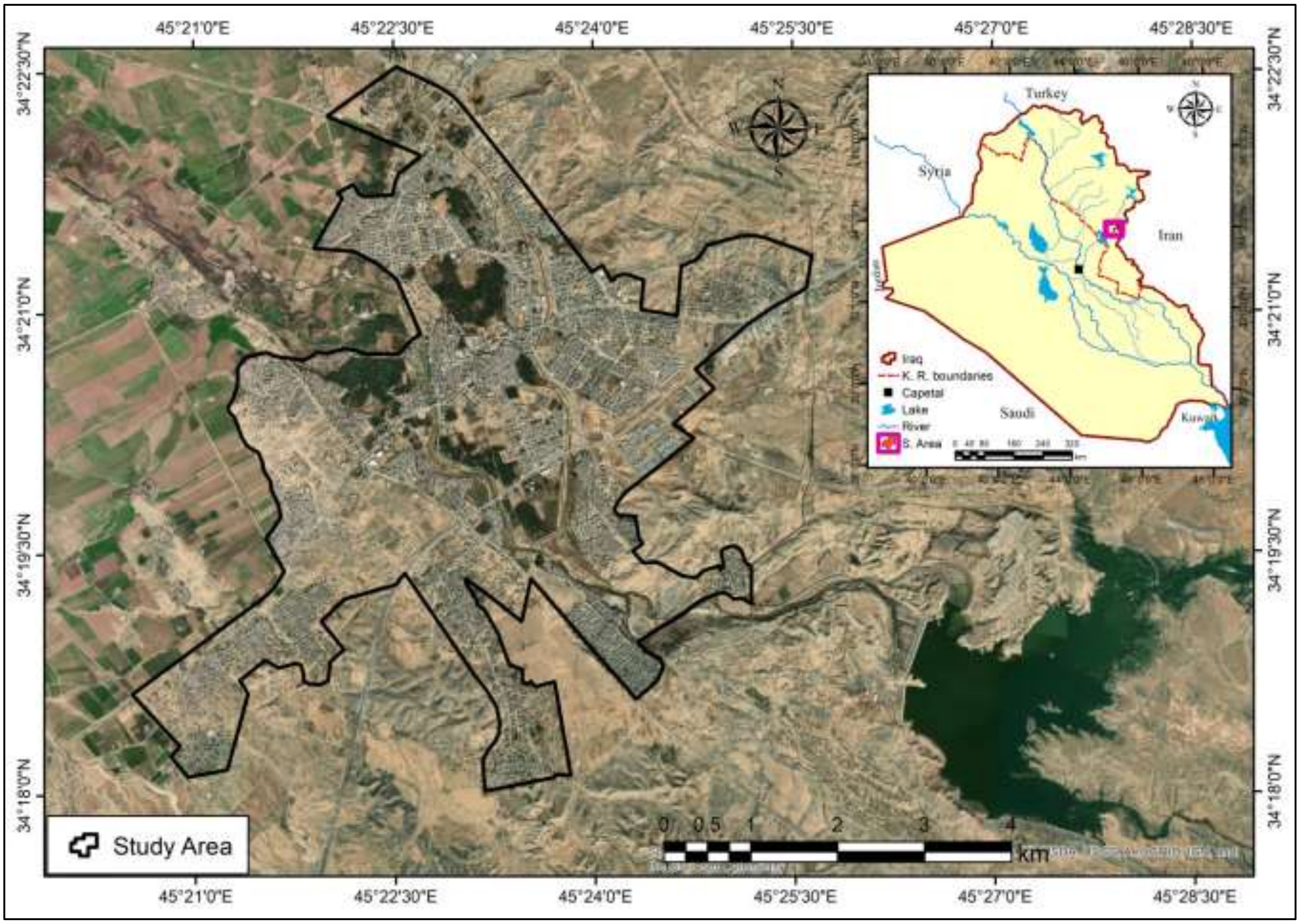
The findings will provide insights into the effectiveness of green spaces in mitigating urban heat during extreme weather conditions and inform future urban planning and environmental management strategies in similar climatic regions. Through this analysis, we seek to enhance our understanding of urban microclimates and contribute to the development of sustainable urban environments.

2. Data and Methodology

2.1. Study Area

Khanaqen city as the study area covers the inhabited areas of the city, it located in South Eastern part of Iraqi Kurdistan region and Eastern Iraq with an area of 26.21 km^2. It lies between latitudes 34° 18′ 02″ to 34° 22′ 32″ North and longitudes 45° 20′ 30″ to 45° 25′ 40″ East. Figure 1.

Figure 1. Location map of the study area



Source: the map prepared using Arc Map 10.8.1 depending on (Esri)

2.2. Data

Landsat 9 images were acquired during the cool wet season (January 2023) and the hot dry season (July 2023). These images, with a resolution of 30 meters, were obtained from the USGS Earth Explorer (http://earthexplorer.usgs.govl) for path 168 and row 036 (Table 1). ArcGIS Spatial Analyst software (version 10.8.1) was used to process the data, retrieve LST and NDVI, and analyze the results.

Table 1. Details of Images used in this study

Image-Scene- ID	Acquisition Date	Acquisition Time	Path / Row	Cloud Cover (%)
LC09_L1TP_168036_20230103_20230315_02_T1	03-01-2023	07:33:40 a.m.	168 / 036	1.35
LC09_L1TP_168036_20230714_20230714_02_T1	14-07-2023	07:33:05 a.m.	168 / 036	0.0

Source: Images properties acquired in Images Metadata from USGS Earth Explorer.

2.2. Methodology

2.2.1. Land surface temperature retrieval

The Mono-Window Algorithm (MW) is a method used for calculating LST from thermal infrared sensor (TIRS) data, particularly from satellite sensors like the Landsat series. It is developed by (Qin et al., 2001), the algorithm focuses on processing the thermal band data to correct for atmospheric effects and surface emissivity variations, which are crucial for accurate LST determination (Wang et al., 2015). In the current study, the MW algorithm was used to derive LST from Landsat 9 data for the study area. Initially, digital numbers (DN) from the thermal band were converted to spectral radiance using Equation 1. Then, the spectral radiance was converted to brightness temperature using Equations 2 and 3. However, to accurately determine surface emissivity, the proportion of vegetation (Pv) values for the Landsat images were extracted from NDVI values, as shown in Equation 4 and

Figure **2**. Subsequently, the emissivity of each pixel in the thermal band was derived using Equation 5. This comprehensive approach ensures that both atmospheric and surface conditions are accurately accounted for, leading to precise LST calculations(Qin et al., 2001) .

$$LST = \frac{BT}{(1+\left(\lambda * \frac{BT}{p}\right)Ln(\varepsilon))} \qquad (1)$$

LST: Land Surface Temperature
BT: Satellite brightness temperature
λ : Wavelength of emitted radiance
ε: Surface emissivity for the used channel.
P: is $h\times c/\sigma$ (1.438×10−2 $m\ K$), where h is Planck's constant (6.26×10−34$J\ s$); c is the speed of light (2.998×108 m/sec); σ is Stefan Boltzmann's constant (1.38×10−23$J\ K$−1).

$$BT = \left(\frac{K2}{Ln\left(\frac{K1}{L\lambda}+1\right)}\right) - 273.15 \qquad (2)$$

K1: Calibration Constant 1 from the meta data.
K2: Calibration Constant 2 from the meta data.
Lλ: Top of Atmosphere Spectral Radiance

$$L\lambda = Ml * Qcal + Al \qquad (3)$$

Ml: Band-specific multiplicative rescaling factor from the metadata
Qcal: Digital number of a given pixels
Al: Band-specific multiplicative rescaling factor from the metadata

$$Pv = \left(\frac{(NDVI - NDVI\ min)}{(NDVI\ max - NDVI\ min)}\right)^2 \qquad (4)$$

$NDVI_{min}$: NDVI value of fully bare pixels
$NDVI_{max}$: NDVI value of completely vegetated pixels

$$\varepsilon = 0.004 + Pv * 0.986 \qquad (5)$$

0.004 : Average emissivity value of bare land
Pv: Proportion of Vegetation
0.986 : Values of average emissivity of the vegetated land.

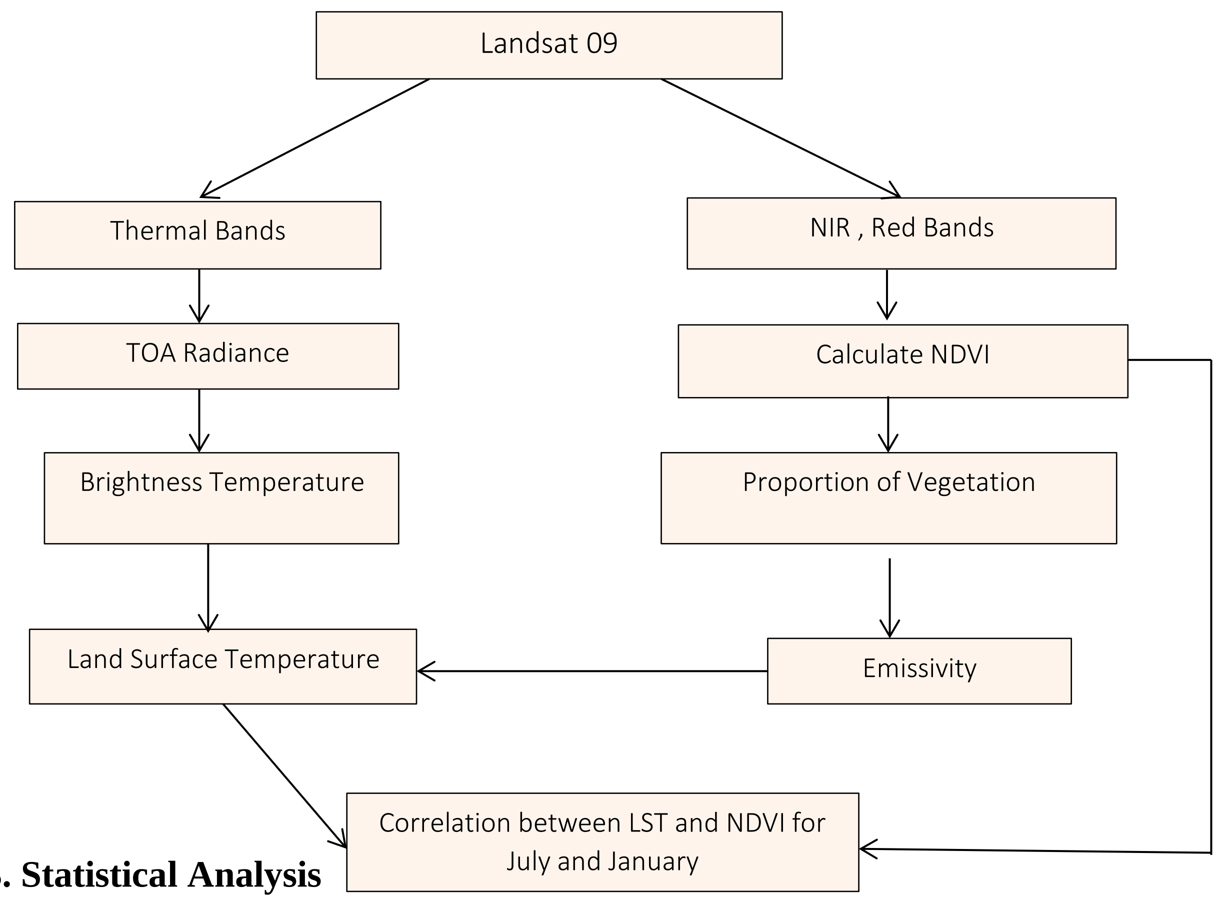
2.2.2. NDVI Calculation

NDVI is a widely used remote sensing index designed to quantify vegetation greenness and health. It is calculated using the near-infrared (NIR) and red light reflected by vegetation (Huang et al., 2021). NDVI helps differentiate between vegetated and non-vegetated surfaces, allowing for accurate estimation of surface emissivity. The proportion of vegetation (Pv) can be derived from NDVI values, which is then used to calculate surface emissivity. This is essential because accurate determination of surface emissivity leads to precise LST calculations. However, by integrating NDVI in LST analysis, researchers can improve the accuracy of temperature estimates and gain insights into the interactions between vegetation and LST. This integration is crucial for environmental monitoring, agricultural management, urban planning, and climate studies (Yue et al., 2007). The study followed the equation proposed by (Rouse et al., 1974) to calculate NDVI:

$$NDVI = \frac{\text{NIR}-\text{Red}}{\text{NIR}+\text{Red}} \qquad (6)$$

NIR : Near Infrared band value
RED: Red band value
Non-existence and existence values ranged from -1 to +1 respectively.

Figure 2. Flowchart shows the methodology



2.2.3. Statistical Analysis

In order to explain the impact of green space on LST, the correlation between LST and NDVI calculated using Pearson correlation coefficient (PCC), that provides standardized measure of linear association between variables, the result ranges from -1 (perfect negative correlation) to +1 (perfect positive correlation) between variables to show the strength of this relationship, and displayed as scatterplot with quantifying this relationship with linear regression. In statistics and data analysis, PCC is frequently used to determine the correlations between variables (Liu et al., 2021). It is especially helpful for evaluating the direction and strength of relationships between distinct elements or variables in invariant fields (Das et al., 2022). The following formula can be used to get the Pearson correlation coefficient (Ahlgren et al., 2003):

$$r = \frac{\sum(\mathrm{xi} - \bar{x})\,(yi - \bar{y})}{\sqrt{\sum(\mathrm{xi} - x)^2}\,\sqrt{\sum(yi - \bar{y})^2}}$$

- r: Pearson correlation coefficient
- xi: Value of the first variable (x) for the i-th data point
- yi: Value of the second variable (y) for the i-th data point
- $\bar{x}$: Mean (average) of the x values
- $\bar{y}$: Mean (average) of the y values

3. Results and Discussion

3.1. Changes of Land Surface Temperature between January and July

Table 2 presents the minimum, maximum, mean, and standard deviation (S.D) of LST for the study area for January and July. During July, the LST values exhibit a substantial range from a minimum of 40.27°C to a maximum of 56.56°C. The mean LST is relatively high at 49.88°C, indicating that the study area experiences significant heat during the summer. The standard deviation of 2.88°C suggests moderate variability in the LST values, implying that while there are some spatial fluctuations, the temperatures are generally high and consistent across the study area. In contrast, January shows a much lower range of LST values, from a minimum of 4.34°C to a maximum of 16.46°C. The mean LST during this month is 12.38°C, reflecting the cooler conditions typical of winter. The standard deviation of 1.43°C indicates less variability in LST compared to July, suggesting that the temperatures are more uniform across the study area during January.

July has a wider spatial temperature range (16.29°C) compared to the January (12.12°C). This indicates greater temperature fluctuations during the July. These findings have several implications for environmental and urban planning in the study area. The high summer temperatures and their variability could impact local ecosystems, water resources, and human health, necessitating the implementation of heat mitigation strategies such as increasing vegetation cover and improving urban infrastructure to reduce heat retention. Conversely, the relatively stable but cooler winter temperatures may influence heating demands and agricultural practices. Overall, understanding these seasonal variations in LST is crucial for developing effective climate adaptation and mitigation strategies tailored to the specific conditions of the study area.

Figure 3. January and July LST map of the study area

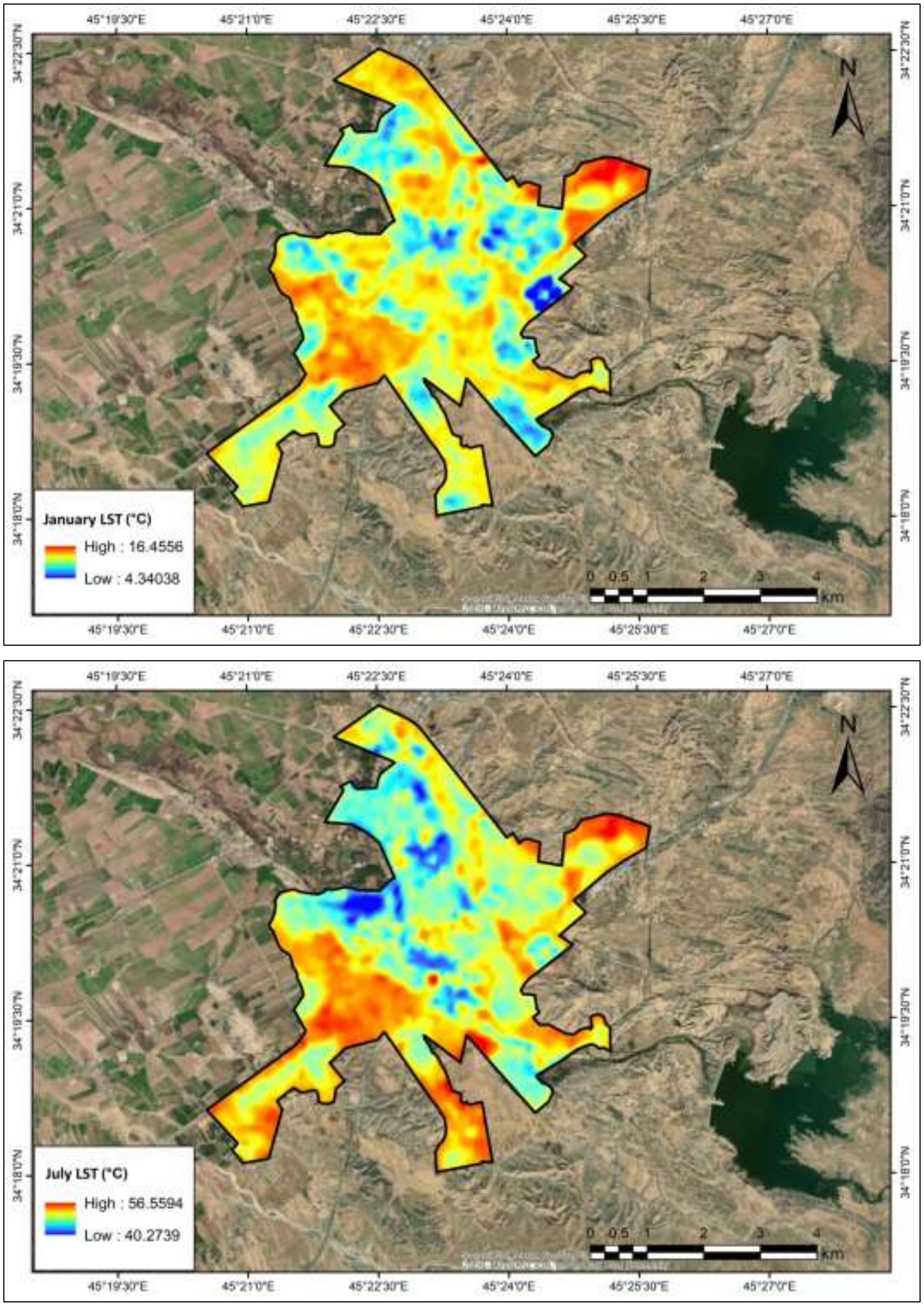


Table 2. Min, max and mean LST for the observation month of the study area

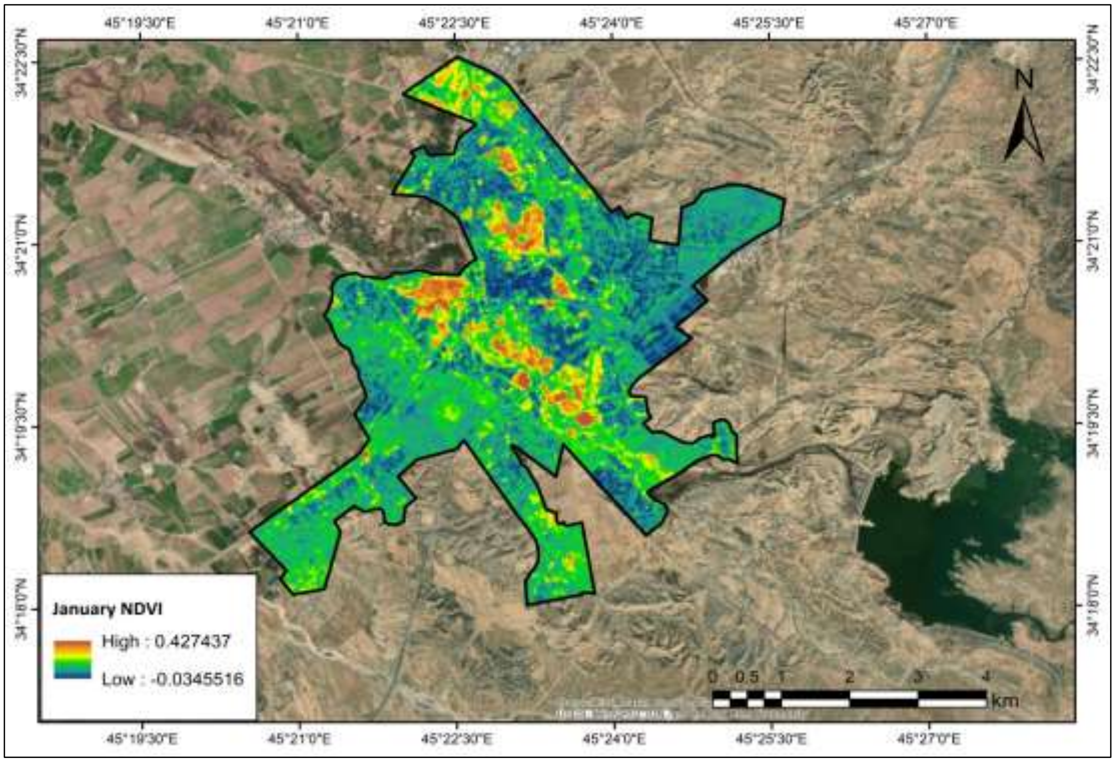
Month	LST (°C)			
	Min	Max	Mean	S.D
January	4.34	16.46	12.38	1.43
July	40.27	56.56	49.88	2.88

3.2. Changes of NDVI value for January and July

Table 3 presents the minimum, maximum, mean, and standard deviation (S.D) of the Normalized Difference Vegetation Index (NDVI) for July and January 2023 for the study area. In July, NDVI values range from -0.01 to 0.45 with a mean of 0.11, indicating sparse or stressed vegetation due to hot and dry conditions. The standard deviation of 0.06 suggests moderate variability in vegetation health across the study area. During January, NDVI values range from -0.03 to 0.43 with a mean of 0.10, reflecting a dormant state of vegetation in cooler months. The standard deviation of 0.05 indicates slightly less variability in vegetation cover compared to July, suggesting more uniform vegetation health.

The NDVI range is slightly higher in July than in January, indicating more variability in vegetation health during hotter months. Mean NDVI values are similar in both months, suggesting overall vegetation cover remains fairly consistent despite seasonal changes. However, higher standard deviation in July points to greater variability in vegetation health and density, possibly due to localized stress or irrigation differences. These findings highlight the need for continuous NDVI monitoring to understand vegetation dynamics, which has implications for environmental monitoring, agricultural management, and urban planning. Integrating NDVI with LST data provides a comprehensive view of land surface conditions, aiding effective resource and environmental management.

Figure 4. January and July NDVI map of the study area



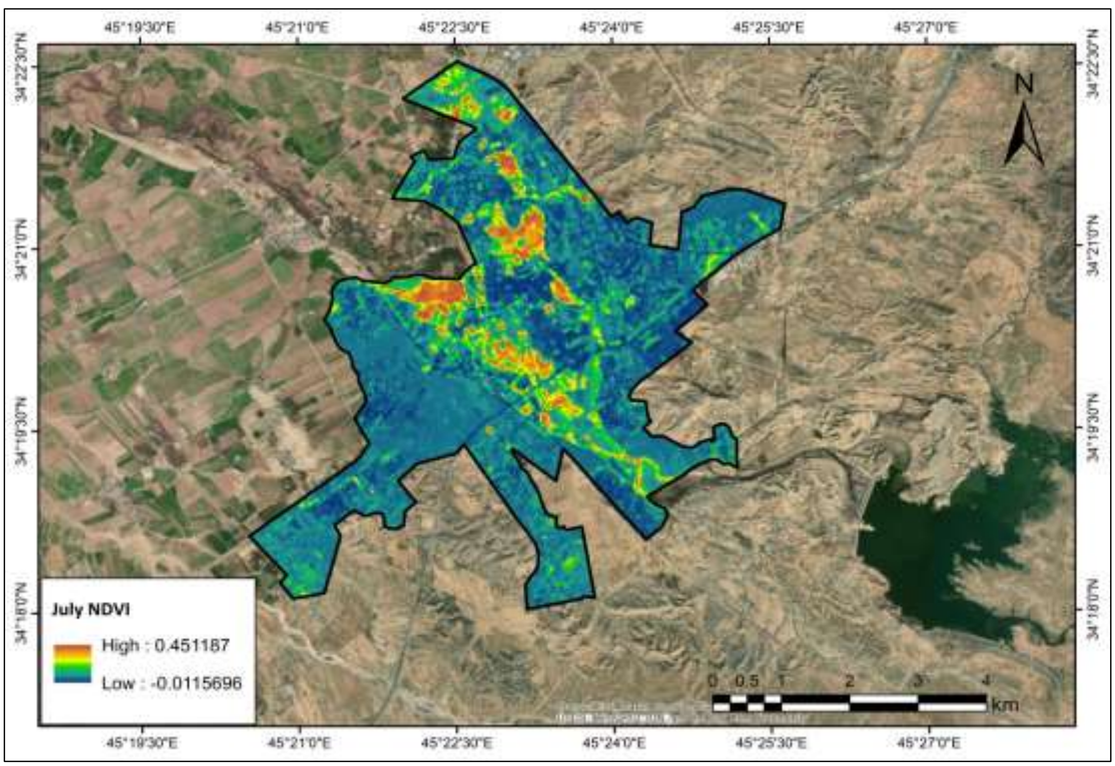


Table 3. Min, max and mean NDVI for the observation month of the study area

Month	NDVI			
	Min	Max	Mean	S.D
January	-0.03	0.43	0.10	0.05
July	-0.01	0.45	0.11	0.06

3.3 Correlation between LST and NDVI for January and July

Researchers have studied the relationship between LST and other variables such as vegetation cover (Favretto, 2018; Grover & Singh, 2015). Table 4 shows that the correlations between land surface temperature and green space vary with seasons. In July, there is a significant inverse correlation between Land Surface Temperature and the Normalized Difference Vegetation Index, with a correlation coefficient (R) of -0.53 and a coefficient of determination (R^2) of 0.28. This indicates that as vegetation density and health increase, LST decreases, with NDVI explaining about 28% of the variability in LST. The statistically significant P value of 0.00 underscores the meaningful relationship between LST and NDVI during July, highlighting the cooling effect of vegetation in hot periods. Maintaining healthy vegetation cover is crucial for mitigating high temperatures.

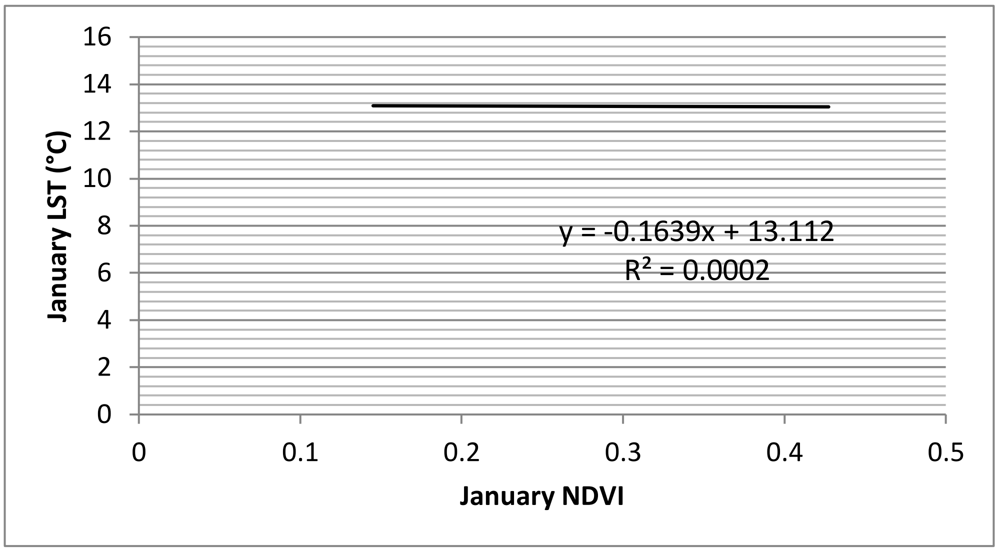
In contrast, January shows a negligible correlation between LST and NDVI, with a correlation coefficient (R) of -0.01 and a coefficient of determination (R^2) of 0.00. The near-zero correlation suggests no significant relationship between vegetation cover and LST during winter. The P value of 0.90 indicates this result is not statistically significant. This lack of correlation is likely due to the dormant state of vegetation and lower temperature variations, which reduce the impact of vegetation on surface temperatures during cooler months.

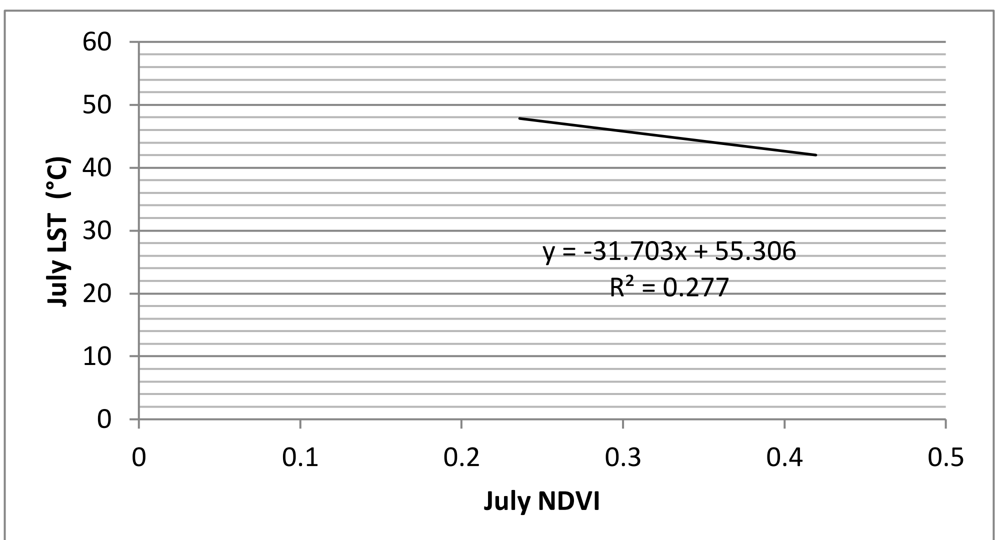
The findings imply that vegetation plays a significant role in cooling the land surface during summer, supporting urban greening initiatives and agricultural practices to enhance vegetation cover and mitigate high temperatures. However, in winter, other factors such as soil moisture and atmospheric conditions might influence LST more than vegetation. These results highlight the importance of seasonal considerations in environmental management and urban planning, emphasizing the need for season-specific strategies to manage LSTs effectively and improve environmental quality.

Table 4. LST & NDVI correlation for the observation month

Month	Correlation Results		
	r	r^2	P value
January	-0.01	0.00	0.90
July	-0.53	0.28	0.00

Figure 5. Regression analysis of the LST and NDVI





4. Conclusion

This study utilized Landsat 9 imagery to analyze the interrelation between LST and the NDVI in Khanaqen City. The findings revealed a significant inverse correlation between

LST and NDVI during July, indicating that areas with higher vegetation cover experience lower surface temperatures. This underscores the importance of maintaining and enhancing vegetation cover to mitigate the effects of high temperatures, particularly in urban areas. Conversely, January exhibited a negligible correlation between LST and NDVI. The study highlights the critical role of vegetation in regulating urban microclimates and the necessity for season-specific strategies in environmental management and urban planning. By integrating NDVI with LST analysis, policymakers and urban planners can make informed decisions to improve the environmental quality and resilience of Khanaqen City. These findings advocate for the implementation of urban greening initiatives and sustainable agricultural practices to enhance vegetation cover, which is vital for mitigating urban heat islands and promoting ecological sustainability.

پشت بەستن بە هەستکردن لە دورەوە بۆ شیکردنەوەی پەیوەندی نێوان پلەی گەرمی ڕوی زەوی و پێوانەی ڕوەک بۆ ساردترین و گەرمترین مانگی ٢٠٢٣ لە شاری خانەقین.

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پوختە

تایبەتمەندی ڕوپۆشی زەوی شارەکان زۆرجار دەبێتە هۆی گۆڕانکاری لە پلەی گەرمی ڕوی زەوی. هەستکردن لە دورەوە (RS) و سیستەمی زانیارییە جوگرافییەکان (GIS) ئامرازێکی گرنگن بۆ بەدەستهێنانی زانیاری ورد سەبارەت بە پێوانە جۆراوجۆرەکانی ڕووی زەوی. ئەم توێژینەوەیە هەڵسەنگاندن بۆ گۆڕانی کاتی پلەی گەرمی ڕوی زەوی (LST) لە شاری خانەقین دەکات، کە دەکەوێتە باشوری ڕۆژهەڵاتی کوردستانی عێراق و ڕۆژهەڵاتی عێراق. ئەم توێژینەوەیە لێکۆڵینەوە لە پەیوەندی نێوان پلەی گەرمی ڕوی زەوی و پێوانەی ڕوەکی (NDVI) دەکات بۆ ساردترین و گەرمترین مانگی ساڵی ٢٠٢٣ بە بەکارهێنانی وێنەی مانگی دەستکردی (Landsat) کە لە (USGS Earth Explorer) وەرگیراوە. ئامانج لەم توێژینەوەیە لێکۆڵینەوەیە لەوەی کە چۆن ڕوبەری سەوزایی کاریگەریی لەسەر پلەی گەرمی ڕوی زەوی

دەبێت لە هاوینی گەرم و وشک و زستانی فێنک و شێداردا. بۆ ئەو مەبەستەش دو وێنەی مانگی دەستکردی Landsat 9 بەکارهێنراون بۆ وەرگرتنی پلەی گەرمی ڕوی زەوی LST و پێوانەی ڕوەکی NDVI بۆ ماوەی توێژینەوەکە. ئەنجامەکان ئاماژە بەوە دەکەن کە ڕوبەرە سەوزەکان بە شێوەیەکی بەرچاو LST لە مانگی تەممووزدا کەم دەکەنەوە، بەجۆرێک کە ئەنجامی شیکاری پەیوەندی گۆڕاوەکان، پەیوەندی پێچەوانەی بەرچاو لە نێوان LST وNDVI، ($R = -0.53$, $R^2 = 0.28$ and P value = 0.00) دەردەخەن. بە پێچەوانەوە، مانگی یەک پەیوەندییەکی کەم نیشان دەدات بەجۆرێک ($R = -0.01$, $R^2 = 0.00$, and P value = 0.90)، کە ئاماژەیە بۆ کەمترین کاریگەری ڕوپۆشی ڕووەک لەسەر LST.

کلیلە وشەکان: ڕوپۆشی زەوی شار، پلەی گەرمی ڕوی زەوی (LST)، پێوانەی ڕوەک (NDVI)، ڕوبەری سەوزایی، هەستکردن لە دورەوە.

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