Emirati Journal of Space and Astronomy Sciences
Vol 2 Issue 1 (2023)
Pages (4 –18)

Available at www.emiratesscholar.com

Estimate Land Surface Temperature in Relation to Land Use Types Using spectral remote sensing data in Koura district

Omar Odat[1], Osama Al-Qawasmeh[2]
omarodat1900@gmail, Osamaalqawasmeh41@gmail.com
Yarmouk University[1,2]

ARTICLE INFO

Published on 28th of May 2024
Doi: 10.54878/pd4w5628

KEYWORDS
GIS, Land Use/Land Cover, NDVI, NDBI, Remote Sensing

HOW TO CITE

Odat, O. ., & Al-Qawasmeh, O. . (2024). Estimate Land Surface Temperature in Relation to Land Use Types Using spectral remote sensing data in Koura district. *Emirati Journal of Space and Astronomy Sciences*, *2*(1), 4-18 https://doi.org/10.54878/pd4w5628

ABSTRACT

Land surface temperature (LST) plays a vital role in global climate change, heat balance, and land use change. Therefore, it is essential to accurately monitor LST over large areas. With the advances in the field of remote sensing, in this study the LST estimation was based on single-channel (SC) algorithm. The study aims to identify the impact of land uses on the LST Koura district in Jordan using geographic information systems (GIS) and remote sensing (RS) during the period (2013-2022), where the supervised classification process was performed and the calculation of algorithms prepared for that, which depends on the analysis of Landsat 8 satellite images. Among the most prominent results of the study is the presence of a large expansion of urban lands at the expense of agricultural and dry lands, with a development rate of 89.4%. As for forests, they witnessed a development compared to what they were in previous years of 31.89%, despite the decline in the area of vegetation cover. The average surface temperature increased during all study periods to reach more than 28 °C in vegetation and dry vegetation. The study revealed a negative relationship between the variation in the vegetation cover index and LST during the study period, while the urban variation index had a positive relationship with temperature. The study recommended the need to take appropriate measures to limit urban expansion at the expense of agricultural lands and work on reclaiming dry lands.

1. Introduction

LST is defined as the temperature that one feels when touching the surface of the earth with their hands or the temperature of the earth's skin. The concept of LST has been widely used by many researchers around the world for temperature fluctuations and vegetation patterns. The surface temperature of the Earth is also the basic climatic parameter in determining surface radiation and energy exchange. LST is a key variable in the processes of surface energy, hydrological balance, and climate change (Li et al., 2013). Accurate measurement and estimation of the LST are considered to be of great importance for many areas of research, such as weather forecasting, ocean circulation, drought monitoring, and energy balance (Allen et al., 2007)

The Earth's LST plays an important role on the Earth's surface it is considered an effective means of global LST monitoring. However, remote sensing data acquisition processes are inherently affected by cloud cover, which leads to varying degrees of data loss in LST products derived from satellites. Climate is considered one of the most important environmental variables that affect the balance of the ecosystem (Hunt et al., 2017). LST is a key estimator of climate, vegetation growth, and urban transformation. It also represents environmental factors that influence land cover patterns using temperature variation across land use land cover classes (LULC). Among these parameters, LULC and LST are the most important. Urban agglomeration is one of the factors that changes land use, alters land cover, or transforms an area (Tariq et al., 2020). The shift in land use and land cover is attributed to human activities that change the physical properties of the Earth's surface and sudden changes in temperature in a particular area (Srivanit et al., 2012). It is well documented that as land cover changes, the surface temperature of that specific area also changes (Pandey et al., 2022)., measuring land surface temperature and its change over a specific period largely depicts the variation in land use and area in that local area.

On the other hand, an important factor that plays a major role in climate change is the rapid population growth that has accelerated the growth of the size of cities through urban agglomeration. The United Nations estimates that more than 60% of the world's population lives in urban areas, and this proportion is expected to increase to 70% by 2050 (United Nations Report, 2015), so Jordan is no exception to this, some governorates have witnessed change, including the capital, Amman, and Irbid Governorate, which are witnessing population growth. The capital is characterized by being the most populous, with a population of more than 4 million people. Irbid Governorate is considered the highest in terms of population density (1,330 people per square kilometer), as the population density is more than double the population density in the capital, Amman (Department of General Statistics 2022).

Previously, various techniques have been used to measure the surface temperature of the Earth from Earth-based data, but this is costly and cumbersome (Zia Ur Rehman et al., 2015). Density time series observations are frequently used in remote sensing RS and LST observational approaches. The accuracy of the spatial resolution 30m of the Landsat 8 images that were relied upon in this research. Landsat 8 instruments represent an evolutionary advance in technology. That collects data for visible infrared (VIR), near-infrared (NIR), and short-wave infrared (SWIR) spectral bands, as well as a panchromatic band (Pan).

Therefore, the current study is planned to investigate LST variation over a wide range of categories and also investigate LULC, including vegetation index (NDVI) and LST. The study area of Koura district was chosen because of its highly diverse topography and erratic rainfall pattern, along with a wide range of land covers such as dry lands, urban areas, vegetation, and forests. To the best of our knowledge, this is the first report to estimate LST and its variance in LULC indexs in the Koura district.

1.1. Objectives of the study

The aim of the study is to find out the effect of LULC on LST by studying the NDVI and urban area index (NDBI) during the years 2013–2022. In the Koura district, where the objective was divided into secondary objectives:

1. Knowledge of land use and land cover LULC in the study area during the period 2013–2022.
2. Estimating LST in the study area using mathematical equations in analyzing Landsat 8 data.
3. Study of the effect of spectral index on LST in Koura District

Ref	Approaches
Doomi et al., 2016	The effect of land cover changes on temperatures in the city of Amman, where the study showed climate change in urban areas, and the results showed a strong relationship between changes in the types of land cover and the surface temperature in the capital Amman, where the remote sensing data of Landsat 5 for the years 1987 and 2003 were relied upon.
Jaber, 2018	The study showed spatial and temporal characteristics and the amount of vegetation through the NDVI and LST. The study period was 1987–2016 using Landsat 5 and 8 data in the Greater Amman Municipality, and the results showed a negative relationship between vegetation index and degrees of heat in the summer and a positive relationship in the winter.
Ibrahim & Abu-Mallouh, 2018	The study indicates the spatial changes that affect the ecosystem and how the actual impact can be made from the local to the global system. This study relied on remote sensing data from Landsat 8 and MODS. The results showed a difference in temperatures for ground uses according to geological factors, and spatial and temporal changes in Earth's surface temperatures can be monitored.
(Taani & Al-Husban, 2022)	This study aims to estimate temperatures over time in Ma'an Governorate, which is considered the largest governorate in Jordan. Adopted Landsat 5 and 8 remote sensing data and determined the relationship between LST and NDVI. The results showed an increase in LST values and an increase in NDVI values, even though the region is exposed to an increase in desertification rates.

Table 1. Examples of different methods that appear in the literature used to estimate LST and their relationship to spectral indices and LULC.

2. Methodology

2.1. Study Area

The study area is located in the south of Irbid Governorate, Koura district, northern Jordan, and Figure 1 represents the location of the study area as this area has a Mediterranean climate, which is described as hot in summer and the average temperature can reach 40. While in winter it's cold and rainy, the average temperature can reach 5 degrees. The study area is characterized by the fertility of its soil and the presence of forests. The primary source for this research is Landsat 8 OLI satellite imagery, which was freely downloaded from the USGS. Data were obtained in May for the years 2013, 2017, and 2022. ENVI and ArcGIS were used to process and analyze statistical visualizations.

2.2. Data collection

Figure 2 illustrates the applied methodology. Firstly, the use of remote sensing data images to implement some operations, the application of index to implement LST equations, and the classification of visualizations to obtain land uses in the study area Estimation of Earth's Surface Temperature: Thermal infrared measurements from Landsat were used to estimate the LST OLI using band 10 as it represents the thermal radiation at the Earth's surface.

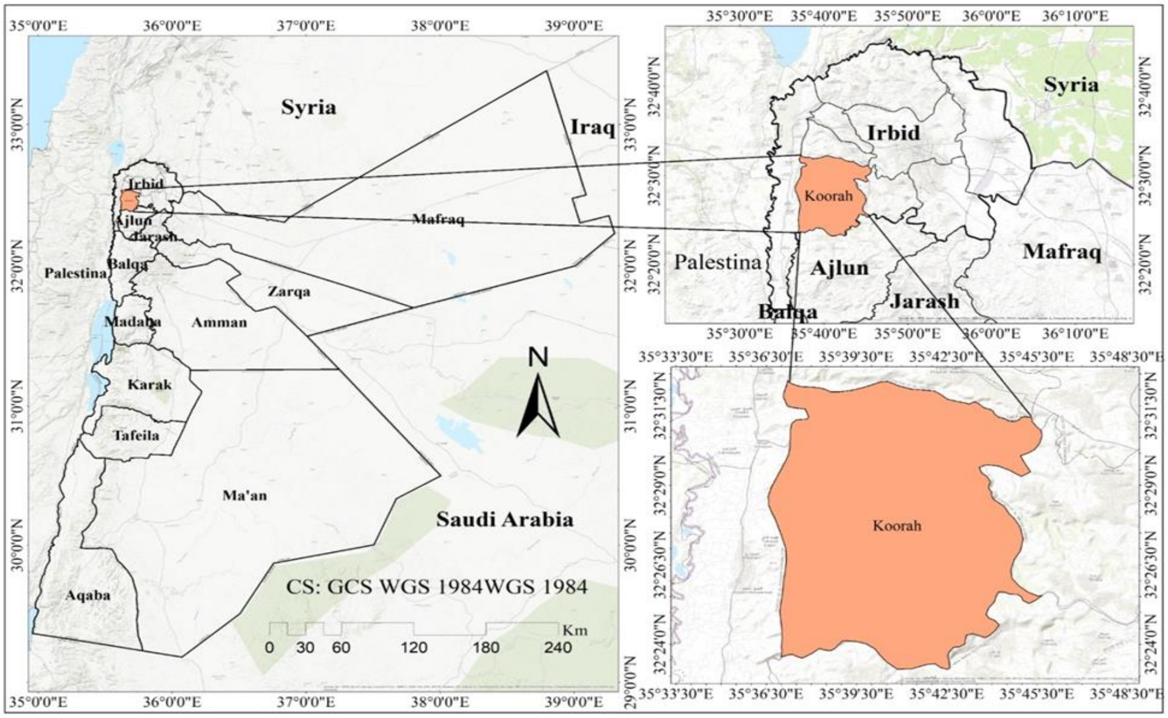

Figure1: Location of study area

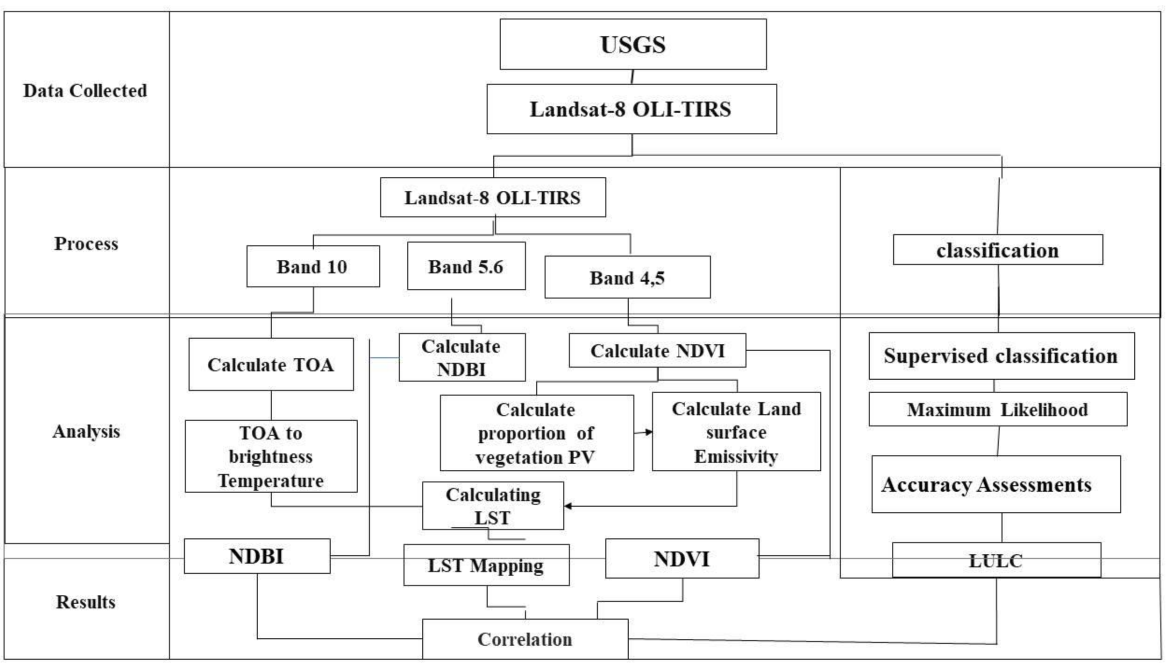

Figure 2: Methodology flow chart of the study

2.3. Image processing

There are several algorithms that can determine the emissivity of the temperature on the earth's surface: single-channel (SC) or dual-angle (DA): The temperature can be calculated from the infrared remote sensing data, SW using Band 10 and Band 11, and DA use single-band Band 10 (Coll et al., 2006).The surface temperature in this study was estimated based on the same SC. SC indexs or algorithms must be calculated to obtain the surface temperature:

1. Conversion to Top-of-Atmosphere (TOA) Radiance

Where ML = radiation multiplicative band 10, Qcal = band 10, and AL = radiance added band 10.

Oi =correction value (for Landsat 8 Band 10, it = 0.29).

Equation (1)

$$TOA=ML * Qcal + AL - oi$$

2. Conversion to Top-of-Atmosphere (TOA) Brightness Temperature: it is not the real temperature of the earth's surface but rather the temperature of the satellite when the image was taken (Alipour-Fard et al., 2003).

Equation (2)

BT= Kelvin (k) to Celsius degree C̊ BT = K2 / ln (k1/L(λ)+1) – 273.15

Where L(λ)= TOA spectral radiance, K1= K1 constant for band10, K2= K2 constant for band10

3. Vegetation Index (NDVI): The vegetation index quantifies the amount of vegetation by measuring the gap between near-infrared light (which is highly reflected by vegetation) and red light (which is absorbed by vegetation). The value of Landsat 8 Band 4 represents red light in the visible rays, and Band 5 represents the near-infrared rays.

Vegetation values range between +1 and -1. If it is an area close to +1, it will be a green area. If the area is close to -1, it is likely a dry area.

Equation (3)

$$NDVI = Float (B5-B4) / Float (B5+B4)$$

4. Portion of Vegetation: The NDVI and proportion of vegetation, through which the degree of emissivity of the Earth's surface shapes can be calculated, are calculated using:

Equation (4)

$$PV = ((NDVI - NDVI\,min) / (NDVI\,max - NDVI\,min))2$$

5. Emissivity: surface Emissivity is a relative factor that estimates black body radiation measured from the surface temperature of the earth.

Equation (5)

$$E = 0.004 * "PV" + 0.986$$

6. Land Surface Temperature (LST): After calculating the previous indexs, it remains to calculate the temperature for the study area based on the following equation:

Equation (6)

$$LST=BT / (1+ (\lambda * BT / C2) * ln$$

Where is BT = Top of Atmosphere brightness temperature C:,λ:=Wavelength of emitted radiance : for Landsat8 Band 10 λ= 10.8, E = Land Surface Emissivity , C2 = h*c/s C2= 14388 m h=Plank's constant = 6.626 * 10-34 m ,

Boltzmann constant = 1.38*10-23 JK

7. Normalized Difference Built-up Index (NDBI):

Index values between -1 and +1, and a negative value represents vegetation or bodies of water. While the positive value represents urban agglomeration areas, noting that the value of vegetation cover for this index is low.

Equation (7)

$$\boxed{NDBI = (Band\ 6 - Band\ 5) / (Band\ 6 + Band\ 5)}$$

Datasets	Data Source
Landsat8	Satellite images

https://earthexplorer.usgs.gov/

Table 3: multiplicative band and Add Band and k1&2 value:

Thermal constant	Multiplicative	Add Band	K1	K2
Band 10	0.000342	0.1000	1321.08	774.89

Table 2: The Landsat 8 satellite descriptions and characteristics.

2.4. Image Classification

Classification is to convert and aggregate the pixels in the satellite image to obtain a digital image and then classify the different land cover. There are two types of classification: supervised classification and unsupervised classification. The classification process is a complex one that requires highly skilled analysts. A supervised classification was used to create the land use map. This technique is used to classify the LULC of the study area and is considered one of the most common classifications.

2.5. Accuracy Assessments

Accuracy evaluation, or validation, is an important step. In order to know the accuracy of the supervised classification and the accuracy ratings, which provide more information about where there are errors, random samples were taken to assess the data, LCLU at each site of the study area, Three standard criteria were used to assess the accuracy of the classifications (overall accuracy, producer’s accuracy and user’s accuracy).

3. Result and discussion

3.1. LST analysis for the Koura district

In this study, the Earth's surface temperature was estimated by a single channel. From the TIRS data from Landsat 8 for the study area during the study periods of 2013, 2017, and 2022 overall, Figure 4 (a) indicates that in 2013, the southeastern regions recorded the highest surface temperature. It is estimated at 33.5°C, and the lowest temperature recorded was 15.48°C. Figure 4 (b) shows the distribution of LST. In 2017, the highest temperature was recorded at 41.5°C and was concentrated in the northeastern parts of the study area. The lowest temperature recorded was 22.88°C. We noticed an increase in temperatures compared to 2013. Figure 4 (c) shows the temperature distribution in 2022, where the lowest temperature decreased to 15.5°C in the southwestern part and the highest temperature was recorded in the southeastern regions around 31.5 °C.

Emirati Journal of Space and Astronomy Sciences
Vol 1 Issue 2 (2023) Pages (42 –55)

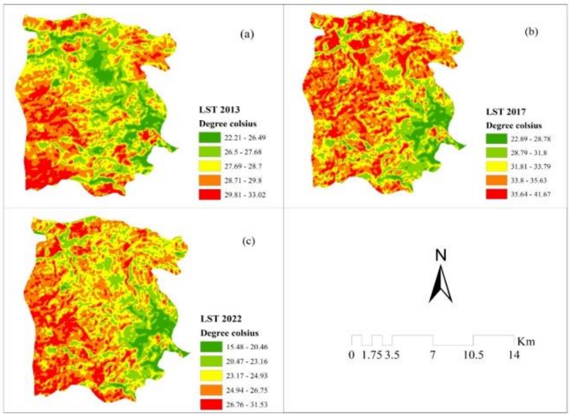

Figure 4: Final estimated land surface temperature of the study area

Table 4 shows the statistical characteristics of temperatures in the Koura district during the study period. It is evident that surface temperatures were higher in 2017 than they were in 2013, reaching 41.6 °C in 2017, while in 2013 they reached 31.5 °C. As for the difference between 2013 and 2022, it was a slight increase, with the upper limit reaching 33.21 °C. However, there was a big difference in the minimum temperatures, as it recorded in 2013 a temperature of 15.48 °C, but in 2022 the temperature increased, reaching 22.21 °C. This confirms the urban expansion in the study area.

LST	Max	Min	Mean	Standard Deviation
2013	33.02	22.21	28.32	2.27
2017	41.66	22.88	33.54	2.51
2022	31.53	15.48	24.56	2.27

Table4: Statistical data for temperature

3.2. Supervised classification of satellite Image used in Koura district:

Based on the estimates of the supervised classification results of the satellite images used in study, obtained classes of land cover and land uses during the study periods extending from 2013 to 2022,It showed the results of the land classification for the study area, As shown in Table3, Where the results of the land classification of the Koura district for the year 2013 showed that the agricultural lands formed the largest extension with an area of 152.6031km2, with a percentage of 85.43%, As for urban areas, they constituted almost 20.39 km2, or 11.42%., As for the areas of forests and dry vegetation , they constitute a small percentage of the area of the study area, as the area of forests reached 5.07, or 2.4%. As for the, Dry vegetation the area amounted to 0.5535, or 0.31%, The results of the classification for the year 2017 showed a development and a wide expansion of urban areas with a rate of change of 58.24%, and a significant increase in dry vegetation with a rate of change of 21.26% from 2013, while agricultural lands clearly declined and the rate of change was 15.27% ,while forests were less in the rate of change by 6.63% It is a small percentage, As for 2022, the urban expansion continued within the study area, with a slight decline of 19.67% compared to 2017, as there was an increase in the area of forests, and the rate of change was 41.2%, As for the rate of change from 2013 to 2022, it shows that there is a significant expansion in urban areas, at a rate of 89.37%, perhaps at the expense of agricultural lands. This is due to weakness in the policies adopted by the concerned authorities in protecting agricultural lands, as for the area of forests; it is increasing significantly, as the rate of change reached 31.89%. As we mentioned earlier, this is due to the efforts exerted in preserving forests through planting trees and limiting cutting them randomly. There are civil society institutions that seek to preserve forests through awareness programs and seminars.

Figure 5 (a) shows the pattern of land use and land cover for the year 2013 in the study area. Where the forests were concentrated in the southeastern part, while the urban areas were larger in the center of the Koura district, and the rest were randomly distributed.

Figure 5(b) shows the pattern of land use and land cover for the year 2017 in the study area, where forests were concentrated in the southeastern part, with a slight decrease in the area of forests compared to what it was in 2013. As for urban areas, they are continuing to increase at the expense of agricultural lands. The dry land area has increase significantly.

Figure 5(c) shows the pattern of land use and land cover for the year 2022 in the study area, where forests were concentrated in the southeastern part, with a slight increase in forest area compared to what it was in previous years. As for urban areas, it continues to increase at the expense of agricultural land and dry lands, which have declined from what they were in 2017.

Year	2013		2017		Change rate from 2013-2017	2022		Change rate from 2017-2022	Change rate from 2013-2022
LULC	Area Km2	percentage	Area Km2	percentage		Area Km2	percentage	percentage	percentage
Urban	20.3931	11.42%	32.2704	18.07%	58.24%	38.619	21.62%	19.67%	89.37%
Forest	5.0742	2.84%	4.7376	2.65%	-6.63%	6.6924	3.75%	41.26%	31.89%
Vegetation	152.6031	85.43%	129.294	72.38%	-15.27%	130.9509	73.31%	1.28%	-14.19%
Dry vegetation	0.5535	0.31%	12.32	6.90%	2125.84%	2.3616	1.32%	-80.83%	326.67%

Table 5: The results of the supervised classification of LULC for the study area during the period 2013–2022

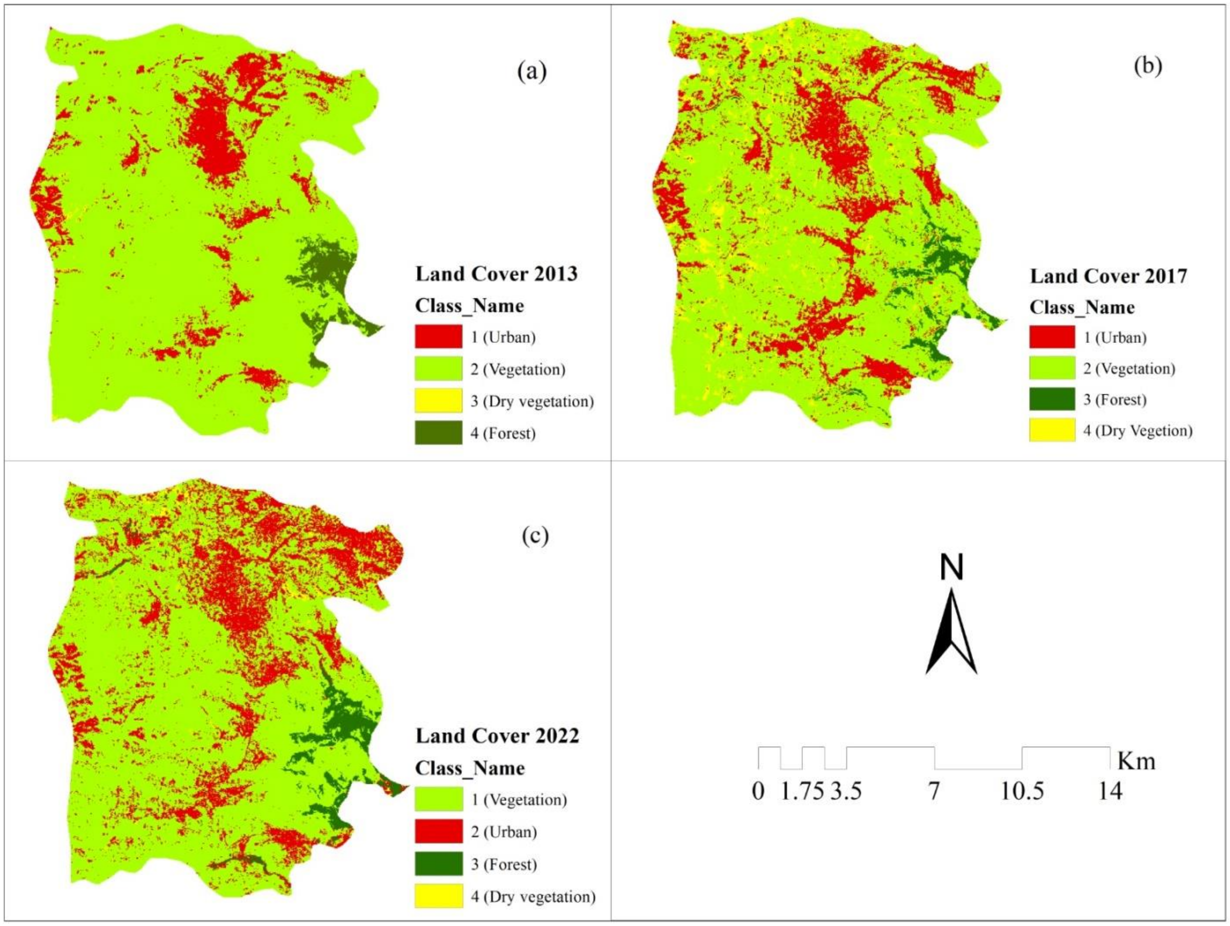

Figure 5: Land Use and land Cover LULC map for the study area (month 5 of each year)

3.3. Analysis of the land cover indexs of the Koura District during periods the study

Figure 11 shows the distribution of NDVI values in the study area. It show an increase in the values during the study periods, with the relative stability of the spatial distribution to some areas in which the index values decreased the valuesof the upper limit increased during the study period. In 2013, the index value reached 0.31. In 2017, the index value increased to 0.52. In 2022, the index value increased slightly reaching 0.55, as for the minimum value, it decreased during the study period. In 2013, the index value reached 0.072. In 2017, the index value reached -0.096, recording a clear decrease from 2013. In 2022, the minimum index value continued to decline, reaching -0.108.

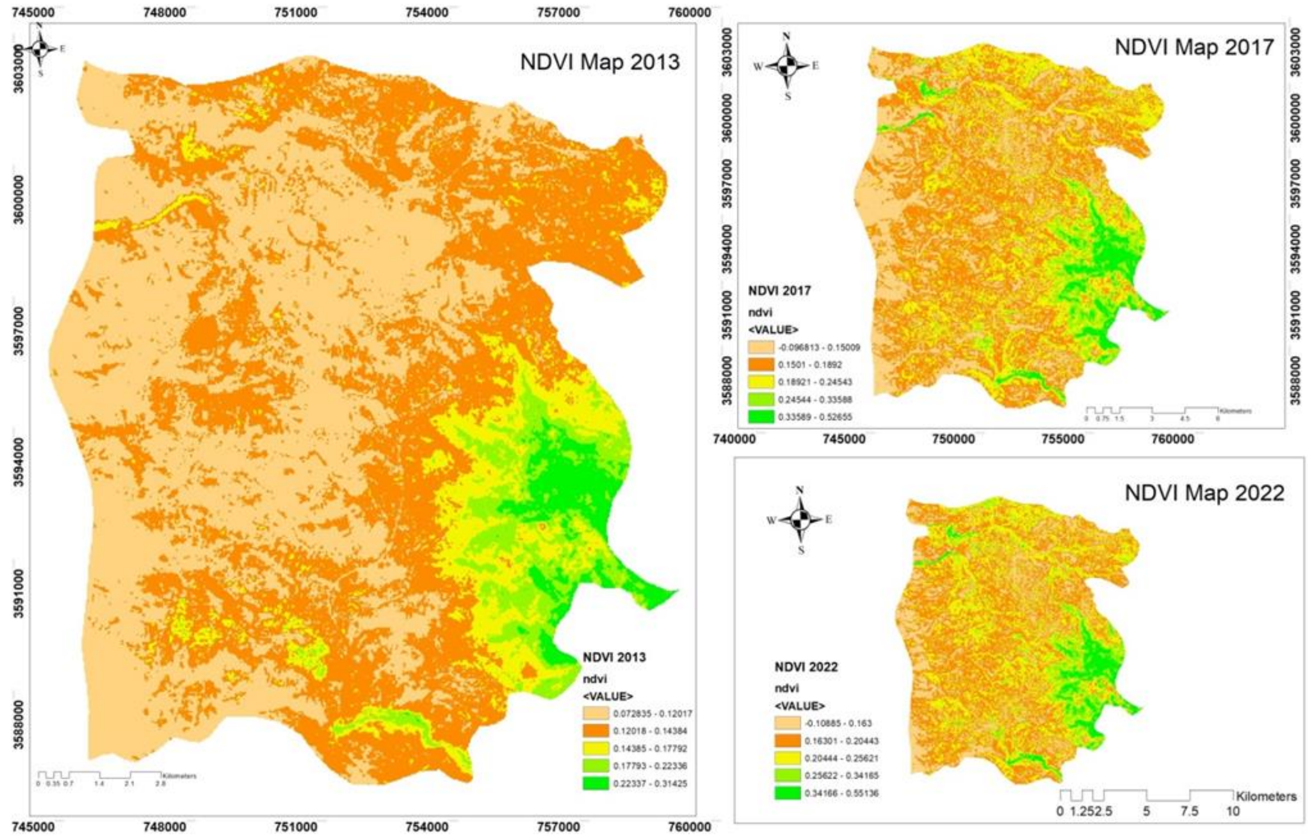

Figure 11: Analysis of spatial distribution of the Normalized Difference Vegetation Index (NDVI)

Figure 12 shows the value of the NDBI index for the study area. The results indicate an increase in the percentage from 2013 to 2022, where in 2013 the value of the index reached 0.046, but in 2017 the value increased to reach 0.112, and the value continued to increase in 2022 to reach 0.137, and this confirms the existence of a large urban expansion that may be at the expense of dry or vegetation

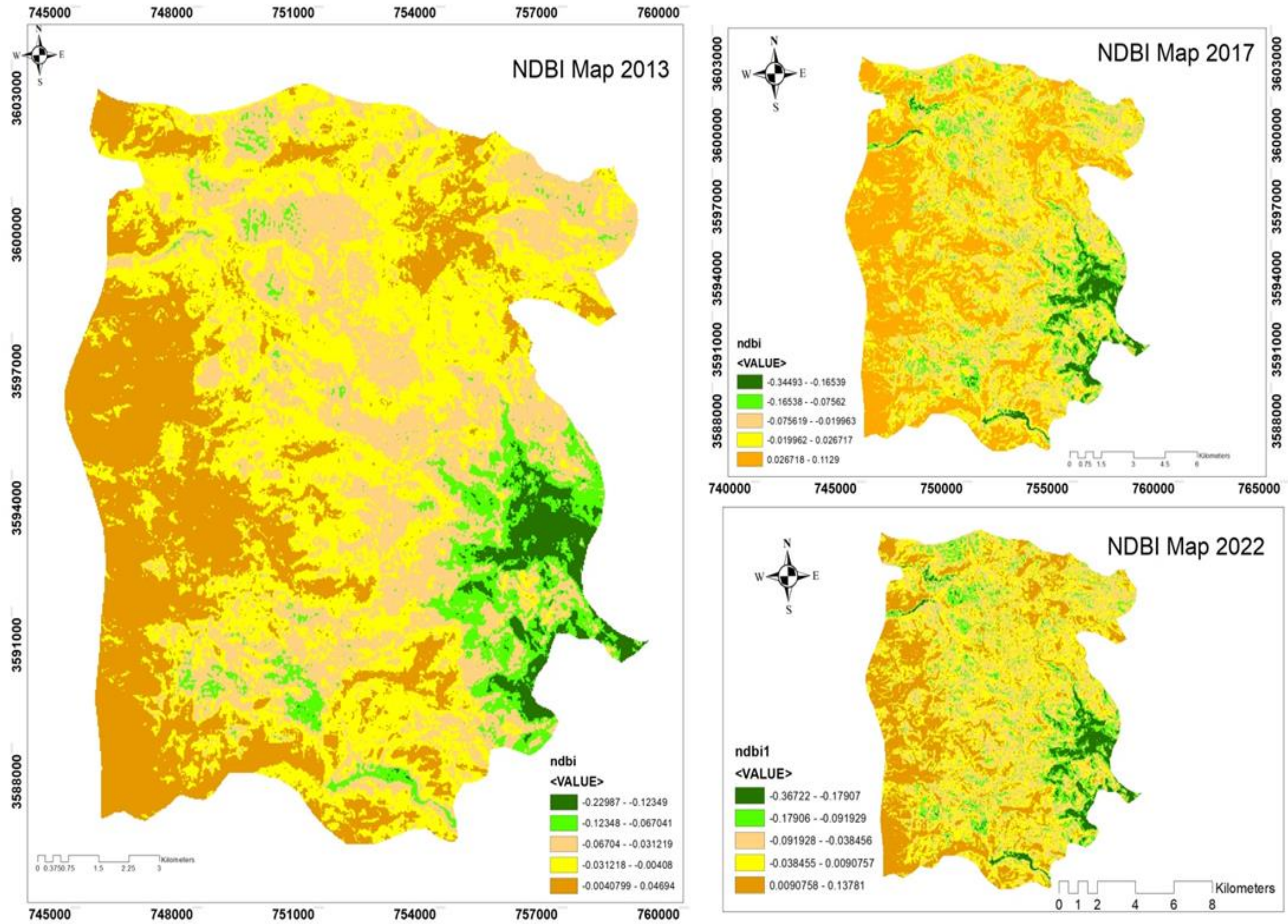

Figure 12: Analysis of spatial distribution of the Normalized Difference Built-up Index (NDBI)

3.4. Analysis of the relationship between spectral indexes and LST in Koura district

Figure 13 shows the linear relationship between the NDVI and the LST which shows an inverse relationship in all study periods

As for Figure 14, it shows the relationship between NDBI and LST, which shows a positive relationship during the study period. Through the linear relationships, it is clear the validity of the results reached by the study regarding the land cover variation on the surface temperature of the study area.

3.5. Analysis of the relationship between temperature and land use in the Koura district:

Table 6 indicates the relationship between LST and land use in the study area, where it is clear that the forests represent the lowest LST, as the average temperature ranged from 23 degrees during the study period, As for the agricultural lands, the temperatures were close during the study period, as the average temperature was 29.27 °C. As for the urban areas, the temperatures varied during the study period, as the average temperature recorded was 31.1°C for the year 2017, while the average temperature during the study period was 27.1°C. The dry lands recorded the highest temperatures, with an average temperature of 32.8°C during the study period. We note that there is a discrepancy in the temperature values for the year 2017. For the years 2013 and 2022, this is due to a change in land uses and an increase in urban expansion at the expense of agricultural lands and dry lands. It is well documented that as land cover changes, the surface temperature of that specific area also changes (Pandey et al., 2022)

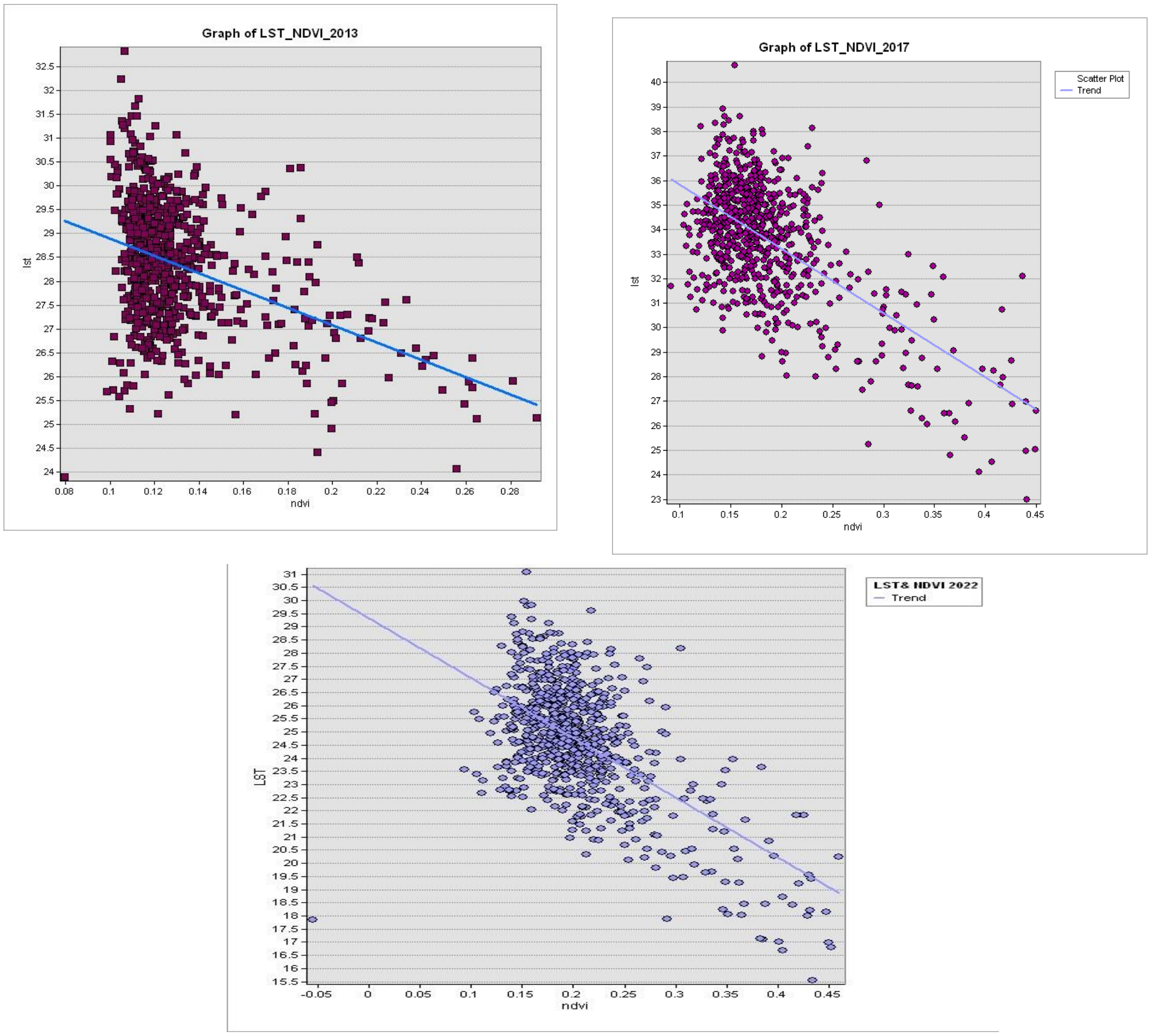

Figure 13: linear relationship between LST and NDVI

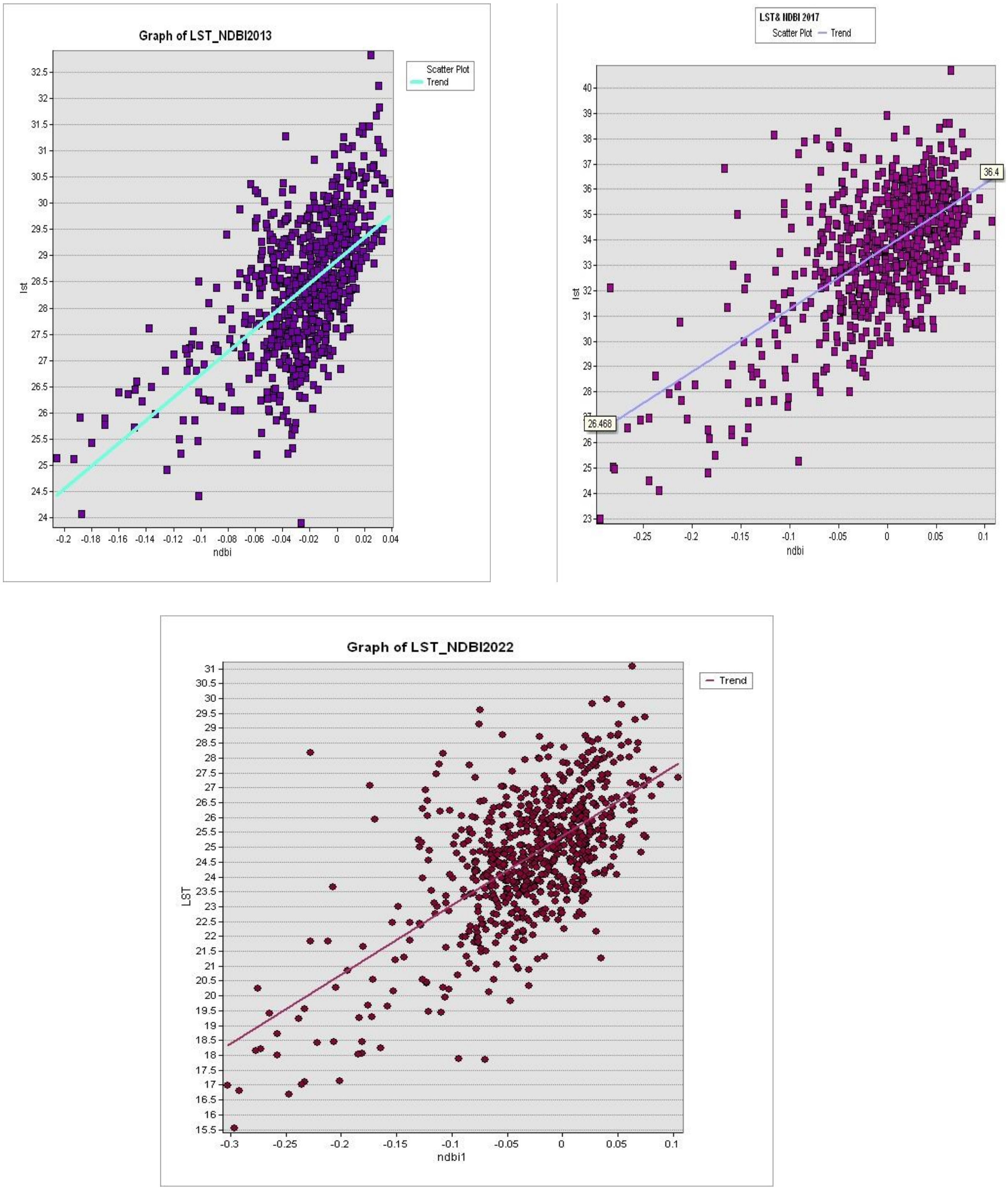

Figure 14: linear relationship between LST and NDBI

	2013			2017			2022		
Class Name	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Urban	27.69	28.7	28.195	28.8	33.78	31.29	20.45	23.98	22.215
Vegetation	28.7	29.81	29.255	33.8	35.62	34.71	23.98	26.75	25.365
Dry vegetation	29.81	33.0255	31.41775	35.631	41.66	38.6	26.75	31.53	29.14
Forest	22.21	26.94	24.575	22.88	28.78	25.83	15.48	20.45	17.965

Table 6: Surface temperature in degrees celsius estimated from Landsat 8 satellite image data

4. Conclusion

The study reached conclusions related to the wide expanses of urban areas, with a rate of change of 89.37% at the expense of other types of land. The largest change rate was for dry lands, as the percentage reached 326.67%, but it has clearly declined from what it was in 2017. As for forests, they remained in balance despite their decline in 2017.The agricultural areas witnessed a significant decline, with a decline rate of -14.19.

Based on the linear regression relationship, the study concluded that there was an inverse relationship between LST and NDVI during the study period, while a positive relationship was found between LST and NDBI, meaning that urban areas may lead to an increase in surface temperatures.

The study recommends the following:

1. Develop regulations and instructions to limit urban expansion at the expense of agricultural lands and forests that may be witnessed in the study area with the increase in population.
2. Conducting a comprehensive and continuous analysis of environmental variables in the study area to monitor environmental and climatic changes in the area.
3. Developing laws to prevent the cutting of forest trees and encouraging voluntary work to plant trees by the local community.

Reference

1. Li, Z. L., Tang, B. H., Wu, H., Ren, H., Yan, G., Wan, Z., Trigo, I. F., & Sobrino, J. A. (2013). Satellite-derived land surface temperature: Current status and perspectives. Remote Sensing of Environment, 131, 14–37. https://doi.org/10.1016/j.rse.2012.12.008
2. Allen, R. G., Tasumi, M., Morse, A., Trezza, R., Wright, J. L., Bastiaanssen, W., Kramber, W., Lorite, I., & Robison, C. W. (2007). Satellite-Based Energy Balance for Mapping Evapotranspiration with Internalized Calibration (METRIC)—Applications. Journal of Irrigation and Drainage Engineering, 133(4), 395–406. https://doi.org/10.1061/(asce)0733-9437(2007)133:4(395)
3. Hunt, J. C. R., Aktas, Y. D., Mahalov, A., Moustaoui, M., Salamanca, F., & Georgescu, M. (2017). Climate change and growing megacities: Hazards and vulnerability. Proceedings of the Institution of Civil Engineers: Engineering Sustainability, 171(6), 314–326. https://doi.org/10.1680/jensu.16.00068.
4. Tariq, A., Riaz, I., Ahmad, Z., Yang, B., Amin, M., & Kausar, R. (2020). Land surface temperature relation with normalized satellite indices for the estimation of spatio temporal trends in temperature among various land use land cover classes of an arid Potohar region using Landsat data. Environmental Earth Sciences, 1–15. https://doi.org/10.1007/s12665-019-8766-2
5. Srivanit, M., Hokao, K., & Phonekeo, V. (2012). Assessing the Impact of Urbanization on Urban Thermal Environment: A Case Study of Bangkok Metropolitan. International Journal of Applied Science and Technology, 2(7), 243–256. http://www.ijastnet.com/journals/Vol_2_No_7_August_2012/26.pdf
6. Pandey, A., Mondal, A., Guha, S., Upadhyay, P. K., & Singh, D. (2022). Land use status and its impact on land surface temperature in Imphal city, India. Geology, Ecology, and Landscapes, 00(00),

1–15. https://doi.org/10.1080/24749508.2022.2131962

7. Zia Ur Rehman, Syed Jamil H. Kazmi, Farheen Khanum, & Zuber Ali Samoon. (2015). Analysis of Land Surface Temperature and NDVI Using Geo-Spatial Technique: A Case Study of Keti Bunder, Sindh, Pakistan. Journal of Basic & Applied Sciences, 11(0), 514–527. https://doi.org/10.6000/1927-5129.2015.11.69
8. Doomi, M. B., Aldayaflah, O., & Hazaymeh, K. (2016). The effects of land cover changes on land surface temperature in Amman; an urban climate change study. Dirasat: Human and Social Sciences, 43(2), 967–977. https://doi.org/10.12816/002843
9. Jaber, S. M. (2018). Landsat-based vegetation abundance and surface temperature for surface urban heat island studies: the tale of Greater Amman Municipality. Annals of GIS, 24(3), 195–208. https://doi.org/10.1080/19475683.2018.1471519
10. Ibrahim, M., & Abu-Mallouh, H. (2018). Estimate Land Surface Temperature in Relation to Land Use Types and Geological Formations Using Spectral Remote Sensing Data in Northeast Jordan. Open Journal of Geology, 08(02), 174–185. https://doi.org/10.4236/ojg.2018.82011.
11. Coll, C., Caselles, V., Galve, J. M., Valor, E., Niclòs, R., & Sánchez, J. M. (2006). Evaluation of split-window and dual-angle correction methods for land surface temperature retrieval from Envisat/Advanced Along Track Scanning Radiometer (AATSR) data. Journal of Geophysical Research Atmospheres, 111(12), 1–12. https://doi.org/10.1029/2005JD006830