The Correlation Among Land Cover Spectral Indices and Surface Temperature Using Remote Sensing Techniques

Aysar Jameel Abdalkadhum¹,², Mohammed Mejbel Salih³, Oday Zakariya Jasim³
¹, Department of Hydraulic Structures Engineering, Water Resources Engineering Faculty, Al-Qasim Green University-Babylon/Iraq.
² Department of Civil Engineering, the University of Technology- Baghdad/Iraq

Abstract. Land cover explains the physical nature of the Earth's surface in a specific area. Land cover is a reflection of the Earth's surface's observable spatial cover comprising complex classes such as agricultural areas, built-up areas, barren lands, forests, water bodies, as well as wetlands. Change detection and monitoring of the land cover assist decision-makers to understand the dynamics of the environmental change to assure sustainability development. Hence land cover feature classification has appeared as a serious research aspect and thus, an accurate methodology for land cover categorizing it became an urgent necessity at this time. This study focuses to find the association between surface temperature and the spectral indices of the land cover. The spectral indices of the land cover such as (NDVI, NDBI, NDBAI, and NDWI) were compared with land surface temperature (LST) and computed the correlation coefficient, just using three images on March 18, July 24 as well as 31 December in 2018, indicating a high positive correlation coefficient among (NDBI, NDBAI) and (LST) and recorded (by built-up areas R= 0.99, R= 0.97 and R= 0.98 ) and (with bare areas R= 0.94, R= 0.98 and R= 0.99), respectively. An inverse correlation coefficient among (NDVI, NDWI) and (LST) where the results recorded a correlation coefficient with (the agricultural areas R= - 0.97, R= - 0.96 and R= - 0.95) and the correlation coefficient with (water bodies R = - 0.93, R= - 0.90 and R= - 0.58) respectively.

1. Introduction
Land-cover/land-use these two terms to describe the physical apparition of the Earth surface over a selected area. They can be used interchangeably, and thus, they be identified comprehensively. The land cover represents the physical cover observed for the earth's surface containing various categories such as water bodies, agricultural lands, vegetation cover, forests, wetlands, and urban areas [1:2]. On the other hand, land use may represent human activities in the present and the future to the earth's surface, which includes commercial, leisure, and industries. Land cover/use is of great importance in scientific research and its various applications as it plays a major role in geographic analysis beginning from the study sciences of Earth to environmental analysis. Therefore, land cover maps must be updated regularly as they are a catalyst between economic and social activities and regional environmental changes [3:4].

[5] were used the multi-temporal of Landsat images of 1989, 1991, and 2000 to retrieve the surface temperature, as well as micro-climate and land-cover relation. The research used multiple indicators, like the NDVI (Normalized Difference Vegetation Index), the NDWI (Normalized Difference Water
Index), the NDBI (Normalized Difference Built-UP Index), and also the Normalized Bareness Distinction Index NDBAI. The results explain increased temperature over both hydrocarbon polluted surface and built-up areas with a negative correlation of surface temperature with NDWI, NDVI, and NDBAI.

[6]. The combination of remote sensing and Geographic Information Structures (GIS) is used in the assessment in addition to research of the land surface temperature (LST) partnership with urban as well as green regions utilizing Landsat-8 satellite images. Vegetation indicators and urban index and the application of assessment of connection as well as the multi-linear regression design for quantitative analysis of urban areas were used. The results showed that urban areas have increased regarding LST in contrast to green spaces, where the temperature increases in urban areas, while the green areas decrease the LST inside urban areas [7].

2. Methodology and data set
Multi-temporal of Landsat images of 18 March, 24 July, and 31 December 2018 to retrieve the surface temperature, as well as land cover spectral indices in three-season (Summer, Spring, and Winter) to find the relationship among them. Four spectral indices are used for this study, these spectral related the most land cover for example (water bodies, vegetation, urban area, and bare land). The goal of this study to investigated and estimated the effect of the temperature on the land cover and help decision-makers to understand change of climate and its impact on the dynamics of the environmental change and urbanization.

2.1 Area of Study
Al-Hashimiya district is a part of the Babylon province, Iraq, which consists of four cities. It is located along the Shatt Al-Hashimiya, while the city of Al-Qasim is located to the south, and Al-Madhatiya and Al-Shomali cities are located to the east. Al-Hashimiya district occupies an area of 1836.74 square kilometers (183674.166 hectares) and it is located to the south of Babylon province approximately between 44° 30′- 45° 15′ E longitude and 32° 00′- 32° 30′ N latitudes as shown in Figure 1. The population of the district is about 600,000 people. It is characterized by its agricultural and rural areas and the moderate weather ranges between the maximum and minimum temperatures (45- 4) °C.

Figure 1: The satellite image on the top right side represents the selected study area with the Iraq map.
2.2 dataset

To describe the climate and investigate the meteorological temperature statement in the study area, the temperature data collected from the Iraqi Agrometeorological network on the same day of Landsat8 satellite acquisition images were used to retrieve land surface temperature and compare it with the meteorological temperature. In this paper used ArcGIS 10.4 to analysis image and LST and land cover spectral indices.

| Date               | Minimum Temperature | Maximum Temperature | Average |
|--------------------|---------------------|---------------------|---------|
| 18 march 2018      | 17                  | 24                  | 12      |
| 24 July 2018       | 32                  | 47                  | 34      |
| 31 December 2018   | 8                   | 19                  | 9       |

3. Results and Analysis

3.1 Land Surface Temperature

To find compatibility between the temperature derived from the Landsat 8 satellite imagery, as well as a handheld ground device for directly measuring the temperature of objects and depend on them in the composition of maps of the classification of the Earth based on the temperature were measured the temperatures of objects in the study area of the various classes of land cover and compare it to the temperature derived from the Landsat-8 satellite. Five images were taken in three seasons during the year which was acquired on the 18th of March, 24th of July, and 31th of December in 2018.

3.1.1 Estimation LST from Landsat8 satellite images

To determine LST from thermal bands of Landsat-8 satellite images that captured one image of the same place in three seasons were used to retrieve LST. The US Geological Survey (USGS) recommended the uncertainties in calibrating band 11 and advised against using it in the LST retrieval process [8]. However, some researchers have obtained satisfactory results when using band 11 [9:10:11]. Because of the starly light effects on band 11 [8], focusing on band 10 to estimate land surface temperature. The land surface temperature maps produce from Landsat-8 images using the mono window method [2:12]. LST maps as shown in figure (2), LST can be calculated using the following equations:

Create a raster dataset
To extract input bands that overlay the study area.
To transform of pixel values to radiance for band 10 as equation (1)

\[
0.00033420 \times \text{"band-10"} + 0.1
\]

(1)

To transform of spectral radiance to at-sensor brightness temperature then convert it from Kelvin unit to Celsius degree for band 10 as equation (2)

\[
(774.8853 / \text{"rad-b10"} + 1) - 273.15
\]

(2)

To calculate NDVI using equation (3)

\[
\text{Float("band-5" - \text{"band-4"}) / Float(\text{"band-5"} + \text{"band-4"})}
\]

(3)

To calculate proportion of vegetation using equation (4)

\[
\text{Square (\text{"NDVI"}-\text{Min. NDVI}) / \text{Max. NDVI- Min. NDVI})}
\]

(4)

To calculate the emissivity using equation (5)

\[
0.004 \times \text{"PV"} + 0.986
\]

(5)
To calculate land surface temperature using equation (6)

\[ B_{t10} / (1 + (0.00115 \times B_{t10} / 1.4388) \times \ln(E)) \]  

(6)

Where: \( b \) is band, \( \text{rad} \) is radiance, NDVI is Normalized Difference Vegetation Index, PV is the proportion of vegetation and \( E \) is emissivity.

3.2 Normalized Difference Vegetation Index (NDVI).

Rouse the first suggested NDVI\([13]\). The NDVI was extracted from the Landsat-8 images band 4 (red (R) ratio: 0.636 0.673 \( \mu \text{m} \)) as well as band 5 (near-infrared (NIR): 0.751 0.879 \( \mu \text{m} \)). The NDVI is by far the most widely utilized index of vegetation as it has an acceptable metric scale ranging from -1 to 1, with 0 as an approximate vegetation-free value. Negative values are areas non-vegetated, whereas values equal to 1 have very dense vegetation. The NDVI is capable of minimizing external noise causes, like topographic impacts and changes in the sun-angle \([14]\). The NDVI were observed to be adaptive to the rainfall, so they have a good relationship. Throughout this analysis, the NDVI algorithm was used to track vegetation modifications, and the NDVI maps can be seen in Figure (3).

\[ \text{NDVI} = \frac{(\text{NIR}-\text{Red})}{(\text{NIR}+\text{Red})} = \frac{(B5-B4)}{(B5+B4)} \]  

(7)

Higher NDVI levels suggest a more stable and abundant landscape. The minimum or even average NDVI values on 18 March, 24 July and 31 December 2018 range from -0.74 to 0.88, -0.23 to 0.73, and -0.45 to 0.78, respectively. In the NDVI, frequent variability arises with changing time, due to evolving land cover assets in the area.

\( \) attained its highest beneficial value on 18 March. The negative NDVI values reflect the current bodies of water or saturated soil throughout the time of analysis. For areas of higher NDVI levels, lower LST was found. Measured NDVI statistics are presented in Table 1. Attaining its highest positive value on 18 March, when the density of fields of wheat is at its maximum. The negative NDVI values reflect the current bodies of water or saturated soil throughout the time of analysis. In areas of higher NDVI values, lower LST was observed, as seen in Figure 3. Measured NdVI statistics are presented in Table 2.

| Date             | Minimum | Maximum | Mean | Standard Deviation |
|------------------|---------|---------|------|--------------------|
| 18 March 2018    | - 0.77  | 0.85    | 0.33 | 0.2104             |
| 24 July 2018     | - 0.23  | 0.74    | 0.22 | 0.11               |
| 31 December 2018 | - 0.46  | 0.79    | 0.282| 0.1610             |

Regions of the desert area, grass, or building generally expression very small NDVI standards, such as 0.1 or below. Sparse flora like grasslands and shrubs will contribute to modest NDVI values, around 0.2 to 0.5. Typically, 0.6 to 0.9 great NDVI values equate to thick vegetation like the one seen in temperate as well as tropical trees or high-growth crops.
Figure 2: LST maps of the study area of 18 March, 24 July, and 31 December 2018
Figure 3: N maps of the study area of 18 March, 24 July, and 31 December 2018
3.3 Normalized Difference Built-UP Index (NDBI)

Proposed the concept of NDBI in automated modeling of urban areas via TM imagery by Zha [15]. The dramatic change in the representation of the built-up region and barren land from band 5 to band 6 was used to differentiate these two bands as normal [15].

\[
\text{NDBI} = \frac{\text{MIR(band6)} - \text{NIR(band5)}}{\text{MIR(band6)} + \text{NIR(band5)}}
\]  

The subsequent values from this analysis indicate values similar to zero for vegetated soils, marginal values for bodies of water and maximum values for built-up areas as well as desert soils. During 18 March, 24 July and 31 December 2018, the minimum and average NDBI values range from –0.43 to 0.29, –0.61 to 0.34 and –0.76 to 0.46 as seen in Figure 4. No major modifications were identified in NDBI. NDBI has a favorable association towards LST, indicating that an change in the built-up environment raises soil surface temperature differences. NDBI not only be used it as an measure for measuring the impact of LST and urban heat islands, but can also offer a robust framework for urban development and design. The estimated NDBI statistics are certain in table 3 the values explain the study of area is sub-urban and agricultural area.

| Date                | Minimum | Maximum | Mean  | Standard Deviation |
|---------------------|---------|---------|-------|--------------------|
| 18 March 2018       | - 0.43  | 0.30    | 0.093 | 0.11               |
| 24 July 2018        | - 0.61  | 0.34    | 0.049 | 0.09               |
| 31 December 2018    | - 0.75  | 0.46    | 0.11  | 0.13               |

3.4 Normalized Difference Bareness Index NDBare (NDBAI)

Zhao and Chen [16] introduced the Sheer immensity index as well as ETM data for simple visualization of bare areas from Landsat TM. The connection is described as follows:

\[
\text{NDBare} = \frac{\text{band6} - \text{band7}}{\text{band6} + \text{band7}}
\]  

For bare surfaces, that in the current case involve desert surfaces as seen in Diagram 5, this connection NDBare is almost always positive. Measured NDBAI statistics is offered in table 4 which is mean there was a few bare area.

| Date                | Minimum | Maximum | Mean  | Standard Deviation |
|---------------------|---------|---------|-------|--------------------|
| 18 March 2018       | - 0.37  | 0.21    | 0.091 | 0.0331             |
| 24 July 2018        | - 0.45  | 0.40    | 0.15  | 0.0521             |
| 31 December 2018    | - 0.41  | 0.41    | 0.181 | 0.07               |
Figure 4: NDBI maps of the study area of 18 March, 24 July, and 31 December 2018
Figure 5: NDBAI maps of the study area of 18 March, 24 July, and 31 December 2018


3.5 Normalized Water Index (NDWI)

Gao developed the idea of NDWI to control the supply of water in vegetation [17]. The reasoning followed is that water absorbs NIR radiation and therefore NDWI should represent its availability in plant leaves.

\[
\text{NDWI} = \frac{(\text{band5} - \text{band6})}{(\text{band5} + \text{band6})}
\]

The sense of the NDWI varies from \(-1\) to 1. Negative or close to zero represent built-up regions or desolate flat lands, while positive values are produced for vegetation cover as well as oil dams which may have any water material. The NDWI can be regarded as an independent measure of plants. This is complimentary to, and not a replacement for NDVI. NDWI was determined to take in the wetlands on the wetland index. The sample area's lowest and highest NDWI index ranges around \(-0.20\) to 0.43, \(-0.34\) to 0.61 as well as \(-0.4\) to 0.75 overall throughout March 18, July 24 and December 31 in 2018 as shown Figure 6. Measured NDWI Statistics are presented in Table 5.

| Date                  | Minimum | Maximum | Mean  | Standard Deviation |
|-----------------------|---------|---------|-------|--------------------|
| 18 March 2018         | -0.30   | 0.43    | 0.090 | 0.1118             |
| 24 July 2018          | -0.34   | 0.62    | 0.05  | 0.09               |
| 31 December 2018      | -0.46   | 0.75    | 0.11  | 0.13               |

4. The Association Among LST and Examined Land Cover Indices.

The relationship between NDVI and LST is depicted in Figure 7. It is illustrated that The NDVI has known to be adversely associated with land surface temperatures. Therefore, the correlation coefficient is obtained as \(-0.97\), \(-0.96\) and \(-0.95\). It specifically shows that the LST is highly associated with NDVI and is negative. While regions with fewer foliage witness higher LST. As shown in Figure 7, the urbanized areas in the research region saw minor development throughout the research era and it can be shown from the NDBI statistical results for the time as seen in Table 2, as observed, the NDBI positive values mean the presence of buildings and roads (asphalt), as well as barren soil. The values were low due to the lack of percentage of residential areas compared to agricultural lands in the study area where negative values mean for vegetation and water bodies. While associating lower LST with vegetation cover, there was a strong correlation between increasing the built-up area and higher LST values, which implies there is a good interaction among the NDBI standards as well as the temperature of the surface of the soil. And as illustrated in Figure 7, the correlation coefficient is obtained as 0.99, 0.97 and 0.98. The longitudinal equation among LST and NDBI shows that much variability in LST values is reflected by the built-up regions. In Figure 5, there is a difference in the expansion of barren soil in July more than December and March as a result of lack of cultivation in this season of the year in the study area. Contrariwise in March, show the decline of barren soil due to the cultivation of field crops such as wheat and barley. Through collected temperature data from meteorological station and comparison with the spatial distribution of the surface temperature, an increase in the barren soil temperature is observed compared to the agricultural areas and water bodies, as well as being less than the temperature of areas with a residential density. A strong positive relationship between NDBAI and LST. Then, the correlation coefficient is acquired as 0.94, 0.98 and 0.99, as shown in Figure 7. The
relationship between NDWI and LST is shown in Figure 7. It is illustrated that the NDWI is negatively correlated with land surface temperature. Therefore, the correlation coefficient is obtained as – 0.93, – 0.90 and – 0.85. This is clearly indicating that the LST is strongly and negatively correlated with NDWI. Hence, areas with the least temperature are experiencing higher NDWI.

Figure 6: NDWI maps of the study area of 18 March, 24 July, and 31 December 2018
Figure 7: Relationship between LST and land cover Indices
5. Conclusions

This study explained the association of the LST with the indices of the land cover, where the relationship among the LST and NDBI, and NDABI was a positive one, whereas the relationship among the LST and NDWI was a negative one. In the area of study, the influence of agricultural areas is more and greater than the water bodies at the land surface temperature, both of which have a negative correlation with the land surface temperature. The reliability obtained in this study by comparing the LST with the surface temperatures of the land cover gives a clear indication of the correctness and reliability of the surface temperature retrieved by remote sensing techniques from satellite imagery which in turn reduces costs, effort and time to obtain information about heat for large areas. The relationship between the land surface temperatures derived from Landsat satellites and the indicators of land cover, gave an indication of the possibility of monitoring many phenomena related to the Earth's surface such as desertification, urban development and expansion, drought and wetlands.

6. Reference

1- Di Gregorio, A. (2005) ‘Land Cover Classification System: Classification concepts and user manual: LCCS’, Food and Agriculture Organization of the United Nations (FAO).

2- Muhammad Mejbel Salih, Oday Zakariya Jasi, Khalid I. Hassoon, Aysar Jameel Abdalkadhum. Land Surface Temperature Retrieval from LANDSAT-8 Thermal Infrared Sensor Data and validation with Infrared Thermometer Camera. International Journal of Engineering and Technology, 2018. 7(4.20) 608-612.

3- Feranec, J. et al. (2007) ‘Corine land cover change detection in Europe (case studies of the Netherlands and Slovakia)’, Land Use Policy.

4- Aysar Jameel Abdalkadhum, Mohammad Mejbel Salih and Oday Zakariya Jasim,’ Combination of visible and thermal remotely sensed data for enhancement of Land Cover Classification by using satellite imagery’ IOP Conf. Series: Materials Science and Engineering, 737 (2020) 012226IOP Publishing.

5- Uddin, S. et al. (2010) ‘A remote sensing classification for land-cover changes and microclimate in Kuwait’, International Journal of Sustainable Development and Planning, 5(4), pp. 367–377.

6- Isa, N. A., Wan Mohd, W. M. N. and Salleh, S. A. (2013) ‘The effects of built-up and green areas on the land surface temperature of the Kuala Lumpur City’, in International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives.

7- Abdalkadhum, A. G. K.; A. J. (2013). Monitoring the land degradation in Mesan area south east of Iraq by remote sensing and GIS techniques. Proceedings of The Second International Conference on Agriculture and Natural Resources, 1019.

8- USGS. (n.d.). Landsat 8 OLI and TIRS Calibration Notices. Retrieved February 15, 2020, from https://www.usgs.gov/land-resources/nli/landsat/landsat-8-oli-and-tirs-calibration-notices.

9- Li, S., & Jiang, G. M. (2018). Land Surface Temperature Retrieval from Landsat-8 Data with the Generalized Split-Window Algorithm.

10- Yu, X., Guo, X., & Wu, Z. (2014). Land surface temperature retrieval from landsat 8 TIRS-comparison between radiative transfer equation-based method, split window algorithm and single channel method. Remote Sensing.

11- Tariq Al-Mansoori, Aysar Abdalkadhum, Alaa S. Al-Husainy. (2020). A GIS-ENHANCED PAVEMENT MANAGEMENT SYSTEM: A CASE STUDY IN IRAQ. Journal of Engineering Science and Technology Vol. 15, No. 4 (2020) 2639 - 2648 School of Engineering, Taylor’s University.

12- Aysar J. Abdalkadhum, Hayder Dibs, Bashar H. Alyasery. (2020). Interpolation and Statistical Analysis for Evaluation of Global Earth Gravity Models Based on GPS and Orthometric Heights in the Middle of Iraq. Iraqi Journal of Science, 2020, Vol. 61, No. 7, pp: 1823-1830.
13- Rouse Jr., J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the great plains with erts. NASA SP-351, 3rd ERTS-1 Symposium.
14- Anyamba, A., & Tucker, C. J. (2005). Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981-2003. Journal of Arid Environments.
15- Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. International Journal of Remote Sensing.
16- Zhao, H., & Chen, X. (2005). Use of normalized difference bareness index in quickly mapping bare areas from TM/ETM+. International Geoscience and Remote Sensing Symposium (IGARSS), 3(August), 1666–1668.
17- Gao, B. C. (1996). NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of Environment.