



Biophysical Impacts of Agricultural Lands on Land Surface Temperature in Karbala Province, Iraq

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Abstract

Agricultural land cover plays a crucial role in regulating land surface temperature, particularly in arid and semi-arid regions such as Karbala Governorate, Iraq. This project focuses on the analysis of changes in spatio-temporal agricultural land in the period 2015 to 2025 and determines how the transformation of agricultural land affects land surface temperature (LST) in western Karbala, Iraq. From 2015 to 2025, agricultural lands will increase considerably with the total vegetation area rising from 32.65 km² in 2015 to 152.75 km² in 2025. Additionally, areas with excellent ecological conditions improved from 18.25 km² to 24.57 km², indicating enhanced environmental stability due to agricultural expansion. The LST trends from 2019 to 2025 show a decrease of approximately 3-4 degrees Celsius for both the center and western areas of this study region. Additionally, mean comparison shows that areas with moderate-to-dense agricultural cover have lower LST than sites with less-than-optimal vegetation. Therefore, a negative relationship between agricultural cover and LST exists. An ecological assessment indicated that there has been a gradual improvement of the vegetation quality of this region, from degraded conditions in 2015 to near-normal conditions in 2025, based upon calculations of vegetation classification and UTFVI values that were less than zero. These findings illustrate how the development of agricultural lands has a substantial impact on temperature intensity and other environmental conditions in arid and semi-arid regions. **Keywords:** Normalized Difference Vegetation Index, Modified Urban Thermal Field Variance Index, Agriculture cover change, Land Surface Temperature.

1. Introduction

Desertification stands as a significant ecological issue impacting arid and semi-arid regions, as it brings about incremental soil damage, loss of biodiversity, increased frequency of dust storms, and a noticeable rise in land surface temperatures coupled with soil quality deterioration. The decline or removal of vegetation cover, whether driven by human activities or climatic fluctuations, intensifies these impacts by rendering the soil surface exposed and highly vulnerable to erosion, moisture loss, and thermal instability¹. Vegetation cover makes a crucial contribution in mitigating the processes of desertification by firming the soil structure, curbing sand movement, and diminishing the severity of dust storms²⁻³. Furthermore, vegetation is essential for regulating the energy balance through increasing shading, enhancing soil moisture retention, and reducing thermal emissions from the land surface⁴. As a result, landscapes subject to tree planting or periodical farming display enhanced tolerance against site-specific climatic variability, standing in stark contrast to unvegetated or arid terrain⁵. Soil heat dynamics serve as a primary ecological gauge owing to their direct link with vegetation cover magnitude, soil water content, and surface composition⁶⁻⁷. The evolution of remote sensing methods, especially satellite-based thermal sensors, has rendered it achievable to accurately delineate Land Surface

Temperature (LST) and assess how vegetation transitions affect the thermal response of soil across time. To this end, the central goal of this research is to numerically quantify the ecological effects resulting from introducing planted forests or seasonal agriculture in previously arid zones⁸⁻⁹. This study seeks to investigate, evaluate, and analyze the spatial and temporal changes in agricultural areas over the last decade within the study area by employing the Normalized Difference Vegetation Index, Land Surface Temperature, and Urban Thermal Field Variance Index using Landsat OLI data from 2015 to 2025. The study further evaluated the thermal regime through satellite-derived LST data to assess the role of vegetation cover in regulating local microclimates and mitigating arid land expansion.

2. Materials and Methods

2.1. Study Area

The area of research extends to the western side of Karbala Governorate, Iraq, and covers the agricultural lands linked to the 'Al-Saqi' project for land reclamation. The area is approximately 209 km², and about 25 km² of it contains 'Al-Saqi' agricultural lands. Geographically, it extends from 32°16' to 32°24'N latitude and 42°09' to 42°18'E longitude. From the topographical perspective, it can be seen that it is a very flat area with no rugged terrain. It is because of these factors that it was identified as a perfect spot for the implementation of an agriculture-based land reclamation project. The western desert parts of the governorate appear similarly low-lying but gradually rise rather slightly with distance southwest toward the southwestern desert margin; local ground surface varies from approximately 17 m up to about 150 m in some western sections, as shown in **Figure 1**. The project began around 2015 after comprehensive soil testing. Based on these analyses, several artesian wells with a targeted depth ranging from 400 to 500 meters were explored to tap water for irrigational use¹⁰. Since then, the land has been put to use for cultivating various plants and species, including dates and barley.

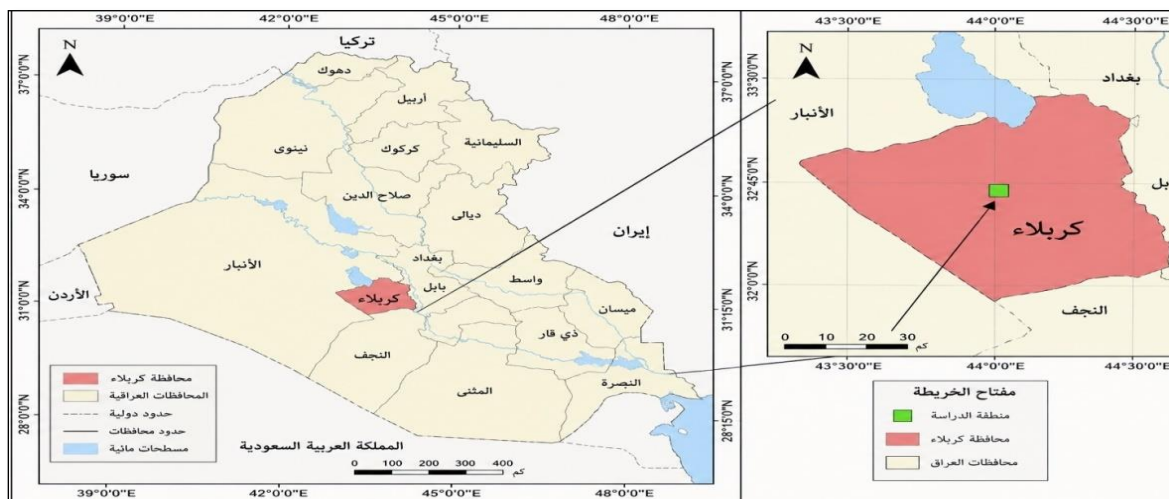


Figure 1. Map of the study area in Karbala Province, Iraq

2.2. Vegetation Monitoring using Normalized Differential Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is an effective remote sensing technique for vegetation quality assessment and space-time analysis of ecological environment change. NDVI takes into consideration the vegetation spectral differences, where high absorption of red light by chlorophyll and interior reflection of leaves in the Near-Infrared (NIR) band exist simultaneously¹⁰. Such spectral differences allow accurate separation of vegetative and non-vegetative regions¹¹. NDVI finds mechanistic application in space-time analysis of vegetation quality, density, coverage, and physiological effects in heterogeneous ecological regions. NDVI analysis in combination with other indices, such as Enhanced Vegetation Index (EVI), highlights higher space-time sensitivity towards vegetation canopy parameters and dense vegetation¹². The

integrated application of the Normalized Difference Vegetation Index and Enhanced Vegetation Index provides an effective approach for accurately distinguishing spatial and temporal variations between vegetated and non-vegetated areas. Comparative analyses have demonstrated significant positive ecological impacts in regions with increased vegetation cover, underscoring the critical role of green spaces in enhancing environmental quality and regulating local microclimatic conditions. Consequently, these indices represent reliable and efficient tools for spatiotemporal ecological assessment and for evaluating the effectiveness of sustainable urban planning strategies in heterogeneous environments¹³⁻¹⁴.

2.2. Land Surface Temperature (LST)

Land Surface Temperature (LST) is a key biophysical parameter used to assess surface-atmosphere energy exchanges and overall environmental conditions. The sensitivity of the LST is high towards land use and land cover changes, especially vegetation density and soil moisture constraints¹⁵. From a physical viewpoint, the factors influencing the evolution of the LST are related to surface energy balance parameters, which involve net radiation, albedo, aerodynamic resistance, and latent and sensible heat flux¹⁶. The effect of vegetation is typically lower because of the high rate of evapotranspiration, which takes a significant portion of the solar radiation energy and transforms it into latent heat energy rather than raising the surface temperature¹⁷. Some non-porous and barren surfaces tend to have higher radiation intensity transformed into sensible heat energy rather than being lost through other mechanisms. The loss of vegetation tends to alter the energy balance and cause higher increases in the land surface temperature¹⁸. Vegetation's density and land-cover changes exert significant influence on surface thermal conditions, as evidenced by the strong inverse relationship between vegetation abundance and surface thermal conditions. Areas characterized by dense vegetation cover generally exhibit lower thermal levels, emphasizing the critical role of green spaces in regulating local microclimates and mitigating environmental stress. In this respect, the combined use of the Normalized Difference Vegetation Index and Land Surface Temperature offers an effective framework for assessing the spatiotemporal variations of the environment and determining how effective urban planning strategies are in helping to alleviate thermal stress¹⁹.

2.3. Data Acquisition and Processing

Satellite imagery was acquired from the United States Geological Survey (USGS), specifically Level-1 products from Collection 2 of the Landsat 8 dataset. Band 10 was utilized for land surface temperature retrieval due to its superior radiometric stability, whereas Band 11 was excluded because of its higher noise level²⁰, as presented in **Table 1**.

Table 1. Acquisition dates and Landsat imagery products with tracks.

Satellite	Sensor	Path	Row	Acquisition Date
Landsat 8	OLI/TIRS C1 Level-1	169	37	2-April-2015
Landsat 8	OLI/TIRS C1 Level-1	169	37	13- April -2019
Landsat 8	OLI/TIRS C1 Level-1	169	37	2- April -2021
Landsat 8	OLI/TIRS C1 Level-1	169	37	8- April -2023
Landsat 8	OLI/TIRS C1 Level-1	169	37	5- April -2025

2.4. Pre-Processing

2.4.1. Land Surface Temperature Retrieval

Landsat 8 OLI and TIRS digital data were used in estimating the Land Surface Temperature of the study region. The TIRS band 10 and Operational Land Imager (OLI) bands 4 & 5 were employed to derive the land surface temperature. The specifications of these bands, as given in the U.S. Geological Survey, Department of the Interior (2016), are given in **Table 2**²⁰.

Table 2. Spectral Characteristics of Landsat-8 OLI Bands

Band	Resolution(m)	Spectral Band	Wavelength(μm)	Solar irradiance ($\text{W}/(\text{m}^2\mu\text{m})$)
4	30	Re (R)	0.630 - 0.680	1574
5	30	Near Infrared (NIR)	0.845 - 0.885	955
10	30	Longwave Infrared (LWIR)	10.60 - 11.19	thermal emission band

The procedure entails the conversion of digital values to top-of-atmosphere radiance, then the estimate of at-sensor brightness temperature²¹. The next step entails the calculation of the Normalized Difference Vegetation Index (NDVI) and the vegetation fraction. Then, the surface emissivity is calculated using an empirical formula as a function of the NDVI. Finally, the Land Surface Temperature (LST) is calculated using the simplified Planck function. The entire process for the LST derivation is depicted in **Figure 2**.

2.4.2. Top of Atmospheric Spectral Radiance (TOA)

The first step of thermal data processing is the conversion of raw digital numbers (DN) to a physical measurable quantity that is, the Top Of Atmospheric Spectral Radiance TOA. It is computed by the formula²²:

$$L_{\lambda} = M_L \cdot Q_{cal} + A_L - Q_i \quad (1)$$

Where: L_{λ} : Top of Atmospheric Spectral Radiance ($\frac{W}{m^2 \cdot sr \cdot \mu m}$), M_L : Band-specific multiplicative rescaling factor, typically extracted from the image's metadata file, Q_{cal} : The Quantized and Calibrated Digital Number (DN) for each pixel, A_L : Band-specific additive rescaling factor (offset), also extracted from the metadata file. Q_i : correction for Band 10.

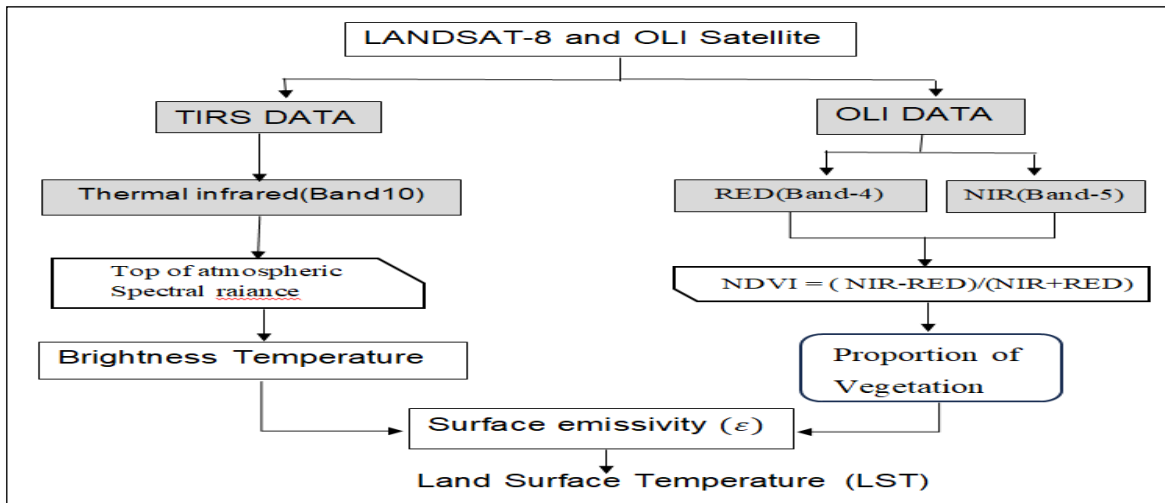


Figure 2. Procedure for Land Surface Temperature Estimation Using Landsat-8 Data

2.4.3. Radiance to At-Sensor Temperature Conversion

By applying the thermal calibration constants from the Landsat-8 metadata file, the brightness temperature is derived from spectral radiance values, which are then converted into at-sensor temperature²³.

$$T_B = \frac{K_2}{\ln\left(\frac{K_1}{L_{\lambda}} + 1\right)} - 273.15 \quad (2)$$

Where: T_B : Brightness Temperature. K_1 and K_2 : Band specific thermal constants, L_{λ} : Top of Atmospheric Spectral Radiance (from **Equation 1**).

2.4.4. NDVI for Correcting Emissivity

The Normalized Difference Vegetation Index (NDVI) is acknowledged for its application in vegetation status analysis and vegetation abundance estimation⁷.

The NDVI formula is as follows²⁴:

$$NDVI = \frac{NIR(\text{band } 5) - R(\text{band } 4)}{NIR(\text{band } 5) + R(\text{band } 4)} \quad (3)$$

Where NDVI = Normalized Difference Vegetation Index, NIR = near-infrared band (Band 5), and R = Red band (Band 4).

2.4.5. Proportion of Vegetation (P_v)

The Proportion of Vegetation (P_v) is essential for the mixed pixel model and LST calculations, as it estimates the fractional area covered by vegetation within a pixel. P_v is calculated from the NDVI using the following formula²⁵

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2 \quad (4)$$

Where: p_v : Proportion of Vegetation in the pixel, $NDVI_{min}$: The minimum NDVI value corresponding to bare soil was set to 0.2, $NDVI_{max}$: The maximum NDVI value representing dense vegetation cover was set to 0.5.

2.4.6. Land Surface Emissivity (LSE)

Land Surface Emissivity (ε) is a critical input parameter in LST estimation algorithms. It quantifies the efficiency of a surface in radiating energy. The LSE was estimated from threshold classification of NDVI according to remote sensing studies. Pixels with $NDVI < 0$ were classified as water bodies and further assigned an emissivity value of 0.991, while areas with NDVI between 0.0 and 0.2 were classified as bare soil with a fixed emissivity of 0.996. Regarding vegetated classes, the threshold of $NDVI > 0.5$ will be assigned an emissivity value of 0.973. The mixed pixel, having its NDVI value between 0.2 and 0.5, has used LSE estimation by an empirical model that is functionally dependent on NDVI. using a simplified relationship for vegetated areas²⁶:

$$\varepsilon = \varepsilon_v p_v + \varepsilon_s (1 - p_v) + C \quad (5)$$

Where: ε : Thermal Emissivity of the land surface, p_v Proportion of Vegetation, ε_v : Emissivity of pure vegetation, ε_s : Emissivity of pure bare soil, C : A cavity term or shape factor related to surface-vegetation interaction (0.005).

2.4.7. Land Surface Temperature (LST)

The Split-Window Algorithm is one of the most common and robust methods for calculating Land Surface Temperature (LST) by effectively reducing atmospheric effects. It utilizes two adjacent thermal bands (T_i or T_f) and incorporates surface emissivity information²⁷.

$$LST = \frac{T_B}{\left[1 + \left(\frac{\lambda T_B}{\rho} \right) \cdot \ln(\varepsilon) \right]} \quad (6)$$

Where: LST: Land Surface Temperature ($^{\circ}C$), T_B : Brightness Temperature, λ : Effective wavelength of the thermal band (10.895 μm), ρ : Constant ($1.438 \times 10^{-2} m$), ε : Land Surface Emissivity.

2.4.8. Modified Urban Thermal Field Variation Index (Modified UTFVI)

Modified UTFVI is computed as a function of the land surface temperature derived from satellite data and can be expressed as²⁸:

$$UTFVI = \frac{LST_i - LST_{mean}}{LST_{mean}} \quad (7)$$

Where: LST_i : Land Surface Temperature ($^{\circ}C$), LST_{mean} Mean Land Surface Temperature of the entire study area.

This formulation, however, has a different interpretation in the context of agricultural expansion in desert environments. In irrigated agricultural areas, the low value of UTFVI normally indicates an improvement of the environmental condition because of cooling due to vegetation and soil moisture, while the higher value may be related to thermal stress, water scarcity, or land degradation³¹ as shown in **Table 3**. Negative or very low UTFVI values show cooling effects associated with irrigation and dense vegetation cover. Moderate UTFVI values represent a thermally stable agricultural system. High UTFVI values can indicate environmental stress due to poor irrigation, soil salinization, or vegetation loss²⁶. The modified UTFVI is strongly influenced by regional climatic conditions, particularly in arid and semi-arid environments. In this context, the study area is an arid to semi-arid region with very hot summers exceeding $45^{\circ}C$

and low annual rainfall (100-150 mm), with mean temperatures of 24 to 27°C, conditions that strongly emphasize the importance of vegetation in reducing thermal stress and improving ecological stability, which is directly reflected in the spatial variation on UTFVI values²¹.

Table 3. Threshold Values of Modified UTFVI and Ecological Evaluation

Modified UTFVI Value	Thermal Condition	Agricultural Thermal Effect	Ecological Evaluation
<0.000	Cooling Effect	Well-irrigated vegetation	Excellent
0.000–0.005	Slight Cooling	Healthy agricultural activity	Good
0.005 – 0.010	Neutral	Stable agro-ecosystem	Moderate
0.010 – 0.015	Warming	Water stress / reduced vegetation	Poor
>0.015	Strong Warming	Thermal stress / degradation	Very Poor

3. Results

3.1. Spatio-temporal Desert Land Conversion Changes based on NDVI

Vegetation indices have been used in remote sensing techniques to estimate the dynamic changes that take place in vegetation cover. In the current study, images obtained from NDVI were employed to determine the extent to which palm trees and crop vegetation exist and are distributed in the desert environment of the Karbala region. An NDVI index slightly higher than zero represents the existence of vegetation cover, while higher values indicate higher density. For this study, values higher than 0.22 were considered moderate vegetation, while values higher than 0.35 were considered to be in healthy conditions. Higher NDVI values (>0.3) can only be found in areas of active vegetation growth, while an NDVI value of between 0.1 and 0.3 would indicate limited to moderate levels of vegetation. An NDVI value greater than 0.5 indicates dense and healthy vegetation cover, reflecting high levels of vegetation productivity and photosynthesis activity per unit area¹⁰. The method of NDVI thresholding was used to classify palm trees and agricultural crops into four different classes, which include dense vegetation, moderate vegetation, sparse vegetation, and other land cover categories. The analysis showed variations in the levels of NDVI from 2015 to 2025. Variation in density of vegetative growth was estimated by studying changes in NDVI values over time and varied vegetation classes. A comparison among NDVI-based vegetative classes is presented in **Figure 3a, b, c, d, and f**.

Total estimated land area with palm trees and agricultural land demonstrates an amplifying trend from 2015 through 2025; in fact, the total land with vegetation has increased more than fourfold over the past decade. The vegetation land areas were measured as 32.65 km², 81.25 km², 111.7 km², 132.17 km², and 152.75 km² in 2015, 2019, 2021, 2023, and 2025, respectively. Areas characterized by sparse vegetation, primarily associated with newly established palm plantations and agricultural activities, indicate an expansion of land allocated for agricultural use and cultivation. In addition, the amount of dense and healthy vegetation for palm trees and crops increased by 16.30 km² from 2015 to 2025. Moderate and sparse vegetation classes were not an exception to this, with an increasing trend, as indicated in **Table 4** below.

Table 4. Area of vegetation density classes (km²) from 2015 to 2025.

Year	Dense Vegetation	Moderate Vegetation	Sparse Vegetation	Total Vegetation	Other Land Use
2015	1.20	6.35	25.10	32.65	175.35
2019	6.45	14.81	60.00	81.25	126.75
2021	11.30	26.90	73.50	111.70	96.30
2023	14.11	33.45	84.62	132.17	75.83
2025	17.5	38.92	96.33	152.75	55.25

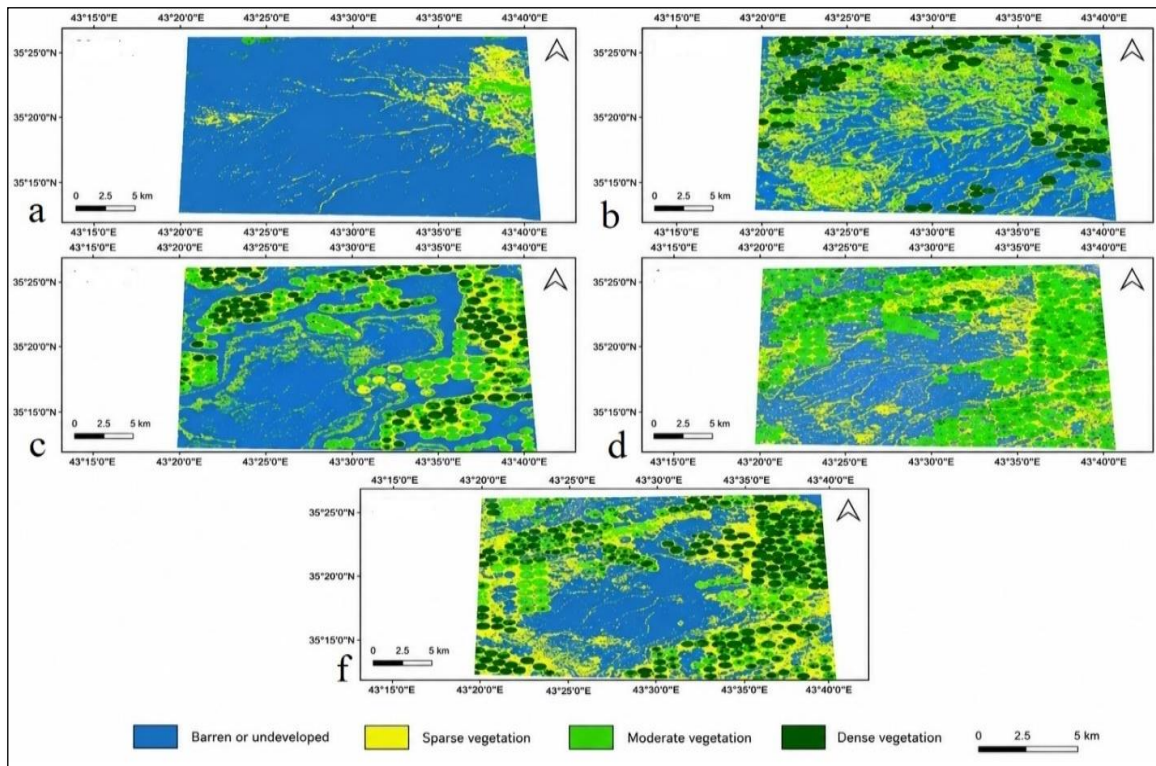


Figure 3. NDVI-classified maps of the study area for 2015 (a), 2019 (b), 2021 (c), 2023 (d), and 2025 (f).

3.2. Land Surface Temperature Distribution

Land Surface Temperature (LST) maps have been prepared to understand the impact of vegetation patterns on temperature variations in the region of study. The variations in LST have been analyzed between 2015 and 2025, as depicted in **Figure 4a** and **b**. In 2015, LST varied between 18.87 °C and 34.12 °C. Later in 2025, it was noticed that LST has risen by 3 to 4 °C, along with a minimum and maximum of 22.45 °C and 37.20 °C, respectively.

High LST values were mostly observed towards the center and west of the study area, where vegetation cover is sparse. Comparing the NDVI and LST maps, it can be observed that the regions with low NDVI levels have higher surface temperatures. Conversely, the regions with moderate to dense vegetation have low LST levels. This clearly explains the inverse relationship between vegetation cover density and LST.

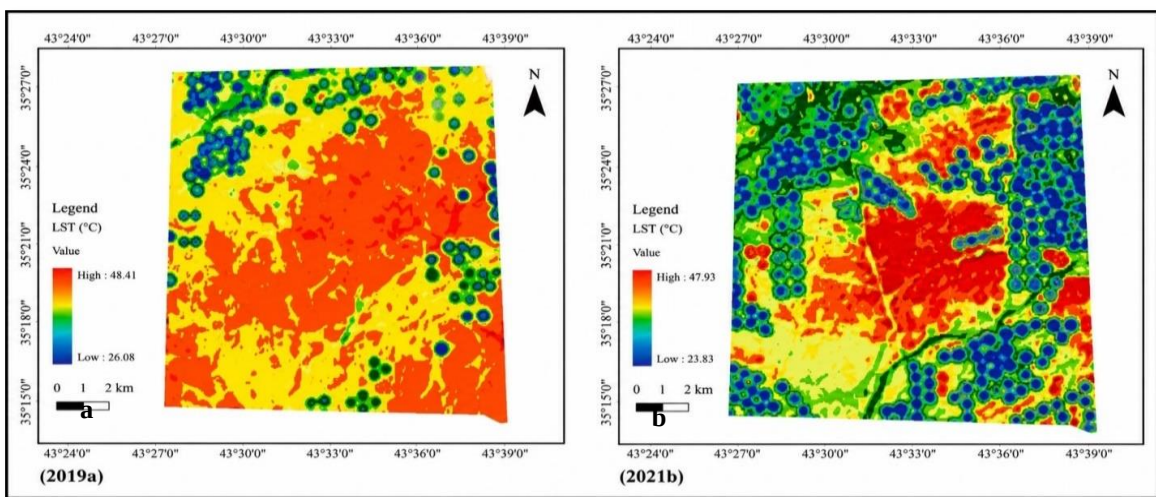


Figure 4. Land Surface Temperature maps of the years a. (2019) and b. (2025)

3.3. Modified UTFVI Field Variance Index Monitoring in Arid Regions

Landsat 8 OLI images were generated and analyzed to assess spatiotemporal environmental changes within the study area. UTFV images for the years 2015 and 2025 are presented in **Figure 5a** and **b**, respectively. By comparing the UTFV threshold values and the ecological evaluation index for these two years, it is clear that there is significant improvement in land surface conditions over the study period. The study area was generally dominated by almost completely barren desert land cover with extremely limited vegetation cover, reflecting poor ecological conditions. However, by the year 2025, the ecological evaluation index indicates a gradual shift toward improved environmental conditions, mostly driven by the expansion of agricultural activities.

For instance, the areas classified under an excellent ecological evaluation category and associated with favorable UTFV values (< 0) increased from 18.25 km² to 24.56 km², indicating significant vegetation cover improvement and hence land productivity enhancement between 2015 and 2025, as shown in **Table 5**. Moreover, the lands of higher UTFV value, which refers to poor thermal and ecological conditions, have been reduced drastically. Land classes under strongly degraded ecological conditions decreased from approximately 5 km² in the year 2015 to about 1.5 km² in the year 2025. It shows the impact of vegetation establishment and agricultural land management on the positive conversion of surface thermal behavior.

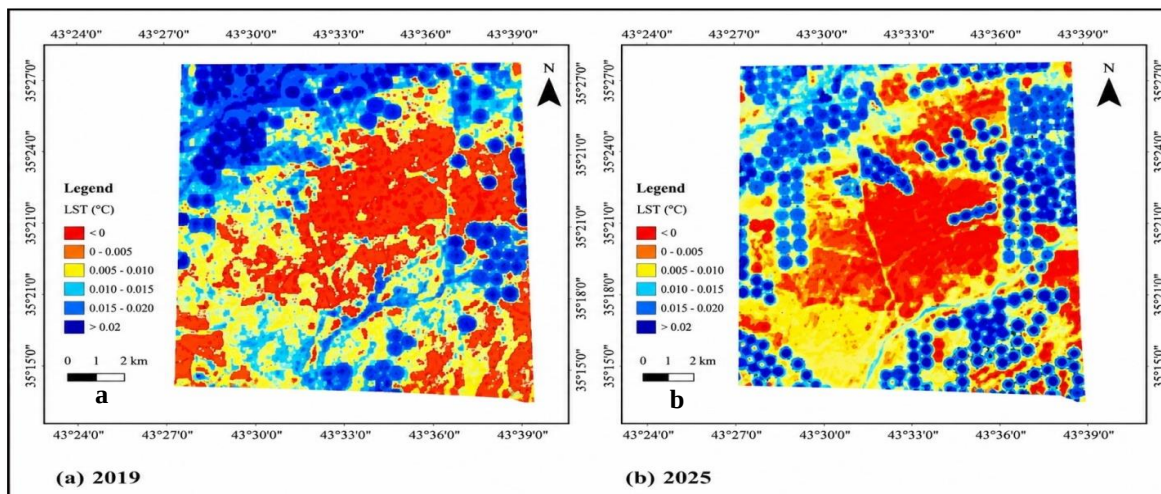


Figure 5. Modified (UTFVI) classification map with ecological evaluation for the years a. (2019) and b. (2025).

Overall, the ecological evaluation index illustrates continuous improvement in vegetative quality and environmental stability, shifting the study area from a predominantly barren desert condition in the year 2015 to a more productive and ecologically balanced agricultural land condition by the year 2025.

Table 5. Modified UTFVI classes with corresponding ecological evaluation for 2015 and 2025

Modified UTFVI Value	Thermal Condition	Agricultural Thermal Effect	Ecological Evaluation	Area (km ²)	
				2015	2025
<0.000	Cooling Effect	Well-irrigated vegetation	Excellent	18.25	24.57
0.000 – 0.005	Slight Cooling	Healthy agricultural activity	Good	7.11	5.27
0.005 – 0.010	Neutral	Stable agro-ecosystem	Moderate	4.65	2.18
0.010 – 0.015	Warming	Water stress / reduced vegetation	Poor	2.69	5.11
>0.015	Strong Warming	Thermal stress / degradation	Very Poor	1.49	2.38

4. Discussion

The results of the Vegetation Cover Index (NDVI) analysis showed that the total area of agricultural land increased from 32.65 km² in 2015 to 152.75 km² in 2025, an increase of nearly five times over ten years, indicating a significant agricultural expansion in the region. The category of dense vegetation recorded a significant increase from 1.20 km² in 2015 to 17.50 km²

in 2025, reflecting a substantial improvement in the health and density of the vegetation cover due to ongoing agricultural reclamation. The medium vegetation cover category showed a gradual growth from 6.35 km² in 2015 to 38.92 km² in 2025, indicating the transition of large areas of land from bare soil to stable vegetation growth stages.

The results of the land surface temperature (LST) analysis showed that the minimum and maximum values increased from 18.87–34.12 °C in 2015 to 22.45–37.20 °C in 2025, reflecting the impact of general regional climate changes. Despite the general rise in temperatures¹⁸, areas with high vegetation density recorded a local decrease in surface temperature ranging from 3–4 °C in 2025 compared to 2019.

The spatial comparison between NDVI and LST maps for the years 2019 and 2025 showed that areas with high NDVI values (>0.35) were characterized by lower LST values than the adjacent desert areas with low NDVI (<0.22).

The results of the adjusted UTFVI index indicated that areas classified within the excellent environmental category (UTFVI<0) increased from 18.25 km² in 2015 to 24.57 km² in 2025, reflecting a clear improvement in environmental and thermal conditions²⁷. In contrast, the area of regions experiencing severe thermal stress (UTFVI > 0.015) decreased from approximately 1.49 km² in 2015 to 2.38 km² in 2025, with a noticeable reduction in the intensity of thermal impact compared to the early years of the study. The results indicate that 2021 represents an important transitional phase, as the total agricultural area exceeded 111.70 km², coinciding with a noticeable improvement in thermal balance and the stability of agricultural systems.

The temporal trends for the period 2015–2025 confirm that organized agricultural expansion has reduced barren areas from 175.35 km² in 2015 to 55.25 km² in 2025, reflecting the success of agricultural reclamation policies in combating desertification.

5. Conclusion

It was made clear that the integrated analysis of land surface temperature (LST), normalized difference vegetation index (NDVI), Modified Thermal Field Variance Index (UTFVI), and the value of the ecological evaluation index has significant potential for the effective assessment of environmental changes in the desert zones. The multi-temporal data analysis of the Landsat satellite images for the period between 2015 and 2025 showed the obvious transition of the studied territory from the condition of a largely bare desert to a condition of a more favorable environment, which has improved because of the further development of vegetation, agriculture, and other land use. The reduction of the land surface thermal stress, along with the growth of vegetation, testifies to the beneficial influence of sustainable land management on the rehabilitation of the desert lands. Moreover, the results showed that the total area of vegetation cover increased significantly from 32.65 km² in 2015 to 152.75 km² in 2025, reflecting the success of agricultural reclamation projects in the region. Dense vegetation also recorded an increase from 1.20 km² to 17.50 km² during the same period, which is a clear indicator of the improvement in ecosystem health. In contrast, bare areas decreased from 175.35 km² in 2015 to 55.25 km² in 2025.

This study empirically reveals the quantitative evidence factoring a change for the better in the conditions of the desert land during the study duration. The satellite images show a significant spread of the vegetation and reclaimed desert areas between the years 2015 and 2025 as the NDVI levels and the modified UTFVI classes decrease. This includes an area supported by a favorable environment (Modified UTFVI<0), which expanded to 6.32 km² more and comprised 24.57 km² of land area by the year 2025, up from the original 18.25 km² of land area in the year 2015.

The Land Surface Temperature Analysis shows a warming trend of about 3–4°C over the region; contrastingly, the results obtained through spatial analysis showed that the locations with the highest NDVI values had lower Land Surface Temperature compared to the sparsely vegetated land in the deserts. The regions that experience poor environmental conditions, with values of

the Modified UTFVI greater than 0.020, showed a drastic reduction in extreme thermal stress zones, declining sharply to almost 0 km² by 2025, compared to 2.10 km² in 2015.

The negative relation between NDVI and LST was evident and supported the assertion that higher vegetation cover in desert areas leads to a local cooling effect and better thermal regulation. In general, the quantitative relations among LST, NDVI, and Modified UTFVI analyses supported the finding that the gradual development of vegetation and the expansion of farmlands have greatly improved the ecological quality and thermal stability of the area under observation over the last decade.

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Conflict of Interest

The authors declare that they have no conflicts of interest with respect to the publication of this manuscript. The authors did not have any commercial or financial relationships that could be interpreted as leading to a potential conflict of interest while conducting their research.

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Ethical Clearance

This research is based entirely on satellite remote sensing data; therefore, it does not involve the participation of human beings, animals, or biological samples. All procedures completed herein were in compliance with institutional research procedures.

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