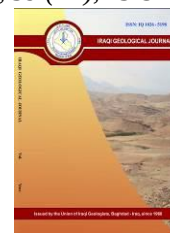




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## Urban Heat Island Dynamics and Urban Expansion in Baghdad: A Spatiotemporal Remote Sensing Analysis (2003–2023)

Khaleel I. Abood<sup>1</sup> , Abdulrahman B. Ali<sup>1\*</sup>  and Shahad M. Ahmed<sup>1</sup> 

<sup>1</sup> Remote Sensing Unit, College of Science, University of Baghdad, Baghdad, Iraq

\* Correspondence: [Abdulrahman.B@sc.uobaghdad.edu.iq](mailto:Abdulrahman.B@sc.uobaghdad.edu.iq)

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### Abstract

The study is related to the Urban Heat Island phenomenon, one of the most important issues that is closely linked to major climate variables. The independent variables used to perform the analysis included urbanization variables and changes in vegetation cover, as well as other factors. The research results indicate a clear, continuous increase in urban land area. In 2003, it was 1251.11 km<sup>2</sup>, equivalent to 28.4%, reaching 1548.12 km<sup>2</sup>, or 35.14% in 2023. This increase is approximately 297 km<sup>2</sup>. As such, the increase is significant, and it significantly affects environmental pollution when combined with the enhanced Land Surface Temperature due to increased anthropogenic heat emissions, cars, and other uses. High temperatures were concentrated in urban, densely populated, and industrially active areas compared to surrounding areas. There is also a rise in temperatures relative to arid (semi-desert) regions, compared with agricultural areas. The correlation with temperatures was positive, when the coefficient of correlation between Urban Build-up Index Normalized Difference Built-up Index and Vegetation Index Normalized Difference Vegetation Index is approximately 0.807, while there is a strong relationship between Normalized Difference Built-up Index and Land Surface Temperature of about 0.837. In 2023, a clear urban heat island pattern is observed in Baghdad due to decrease vegetation significantly associated with an increase in built-up areas during the period from 2003 to 2023.

**Keywords:** ASTER; Spectral Indices; LULC; Correlation Matrix; Baghdad City

### 1. Introduction

Urbanization is one of the most important factors behind the changing climate pattern across the world (Chai et al., 2022). In recent decades, changes in land use and land cover, as well as a decline in natural land cover, have significantly altered the climate of urban areas (Oli et al., 2025). The rapid change in land use and land cover (LU/LC) is attributed to the continuous growth of urban populations (Gupta et al., 2020). Urban populations are increasing at a rapid rate, especially in developing countries, due to continuous migration from rural areas in search of better job opportunities. The continuous increase in urban populations has led to the conversion of natural land cover surfaces into land use types (anthropogenic LU/LC) for the purpose of expanding industrial, commercial, and residential areas (Bozkurt et al., 2023).

Baghdad has witnessed significant geographic changes in its main land covers in recent years due to population growth as well as migration from rural areas to major cities, and the thermal contrast within the city is now known as the heat island, which is one of the important phenomena that has come

to represent accurate measurements for deducing areas that experience an increase in temperatures in order to address its causes later through detailed studies. The measurements taken by (Nassif et al., 2020) after 2003, which can be defined as the contrast in the increase in temperatures in large industrial and residential cities compared to rural areas, and the urban heat island develops spatially and temporally as a result of a set of factors within the city, which are linked to the state of the city itself, including the number of inhabitants, cars, industrial machinery, and other activities, and its atmospheric envelope (Peng et al., 2018).

The urban heat island effect contributes to global warming and increases as one moves deeper into it (Meng et al., 2018), reaching its peak in the city center and areas with industrial activities associated with fuel combustion (Raihan, 2023) for industrial areas. There are also natural factors that lead to a significant increase in land surface temperature, which leads to the creation of a local climate that differs significantly from the climate of adjacent agricultural areas. Human (population) increase is followed by human activities with different energy uses such as heating, fuel combustion, establishment of factories, transportation, which in turn lead to an increase in temperatures (Ghoniem et al., 2025) and facilities in cities compared to agricultural (rural) areas (Tayyebi et al., 2018).

The only indicator for measuring the energy balance on the Earth's surface to measure temperatures is the climate variable Land Surface Temperature (LST), as it is considered a key variable in the processes of radiative exchange between the air and the Earth's surface. The radiative exchanges between the surface and the surrounding air are a measure of energy fluctuations and atmospheric interactions, which affect the efficiency and speed of exchange processes between components, and thus can be used to identify hot spots (Zou et al., 2021). This is where the correlation between the (LST) coefficient and urban growth comes into play, which is associated with areas with solid surfaces that have greater thermal capacities than vegetated surfaces, where part of the solar radiation energy is converted into heat. While in the vegetation cover, part of the solar radiation energy is converted into energy that contributes to evaporation from plant leaves, leading to a decrease in air temperatures around it through humidity (Clelland et al., 2024).

According to Hashim et al. (2022), There are always significant differences between artificially impermeable and naturally permeable surfaces in terms of ground surface temperature (LST) due to their differing thermal properties. The results show that climate change and urbanization contribute to rising surface temperatures and the formation of urban heat islands. The increase in temperatures was 5°C over 36 years. The study is "Impact of land surface changes on air temperatures in Baghdad between 2000-2015", where the thermal climate was affected by the rate of urban growth. In the study by Jasim Al-Jiboori, "Spatiotemporal impact analysis of variables on Baghdad city" (Al-Jiboori et al., 2020), in a case study of land surface in the northeastern part of Baghdad province, Iraq, between 2000-2024, this study showed that temperatures were 34.78°C, increasing to an average of 40.25°C, with minimum temperatures ranging from 26.29-33.66°C and maximum temperatures from 41.14-48.25°C (Jasim, 2025).

Researchers in Basra studied the impact of environmental variables on land surface temperature. The results of these studies indicate a positive relationship between land surface temperature and vegetation cover; the greater the vegetation cover, the lower the land surface temperature. They found that more vegetation cover means lower temperatures and urban density means higher temperatures (Tawfik and Al-Lami, 2025).

In line with Iraq's Vision for Sustainable Development 2030, this research primarily aims to analyze the impact of environmental factors on the urban heat island phenomenon in Baghdad, a common strategy for mitigating heat. This analysis relies on spectral indices directly related to surface temperature, namely the NDVI and NDBI indices, and how these indices change depending on surface conditions and the city's distance from green spaces, employing a correlation matrix.

## 2. Urban Heat Island (UHI)

The study of urban heat islands relies on surface temperatures, as higher temperatures increase the prevalence of the urban heat island phenomenon (Khalaïm et al., 2021). Geographical location has a significant impact on defining the characteristics of diverse geographical areas, as it is a crucial environmental element in determining the geographical boundaries of urban heat islands (Singh et al., 2017). Climate directly affects urban heat islands; temperature is one of the most important climatic elements influencing them, as it is linked to all other climatic elements, such as atmospheric pressure, wind, humidity, and rainfall (Petrou and Kassomenos, 2024). This thermal variation leads to the formation of thermal islands, as a result of the difference in their climate compared to the surrounding rural areas.

Humidity affects the air's ability to conduct and store heat. Humid air retains heat more readily than dry air, which in particular affects surface temperatures. Evaporation from water surfaces and transpiration from plants also play a role in surface cooling (Kassomenos et al., 2022). In heat island areas, buildings, roads, and other infrastructure replace open land and vegetation. This means that most of these materials have the ability to absorb solar radiation and convert it into heat energy, increasing the temperature of the surrounding environment (Verdonck et al., 2018). Urban heat islands are usually around all the time, but tend to be strongest during the day when the sun is shining (Petrou and Kassomenos, 2024). During the summer, the sun can heat exposed surfaces, paved roads, and buildings, and their temperatures can reach very high levels, ranging between 27 and 50 °C (75-95 °F), which are hotter than the air, meanwhile, shaded or humid surfaces often in the surrounding countryside remain close to the air temperature (Jabbar et al., 2023), as shown in Fig. 1.

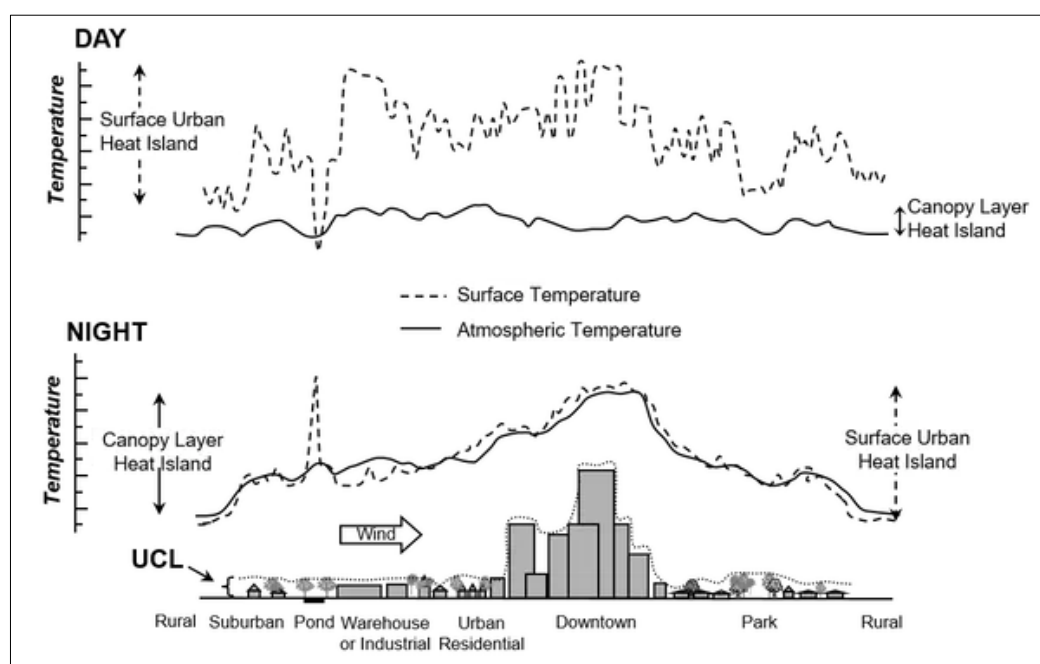
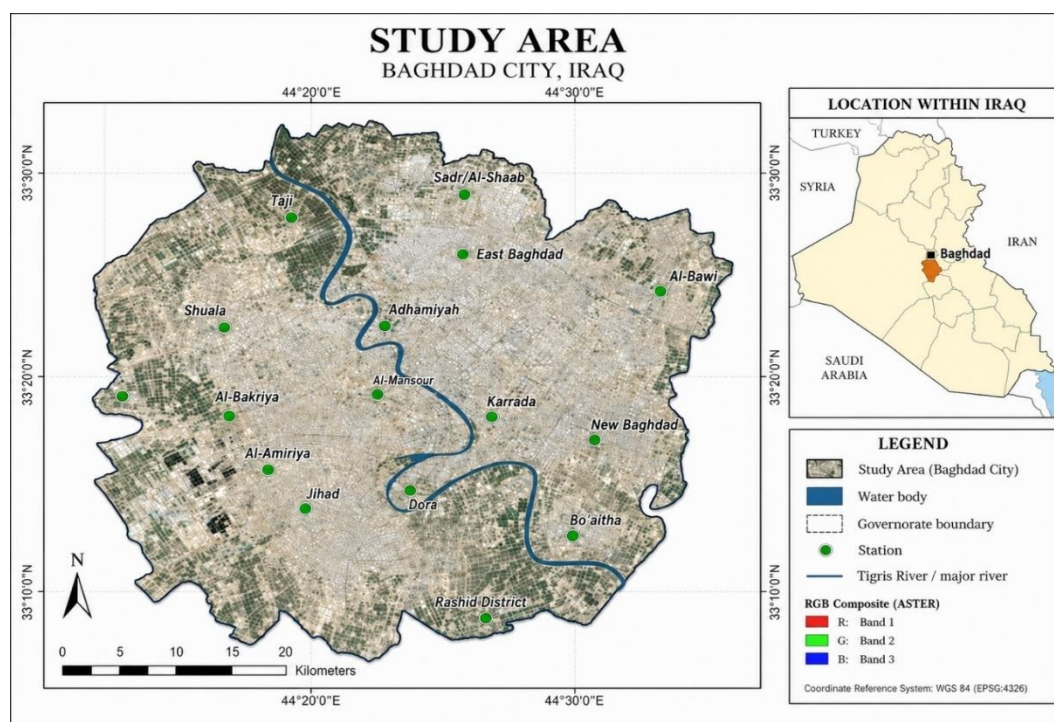


Fig. 1. Urban heat island profile: Surface vs. atmospheric temperature during day and night across urban-rural gradient (Amorim et al., 2021)

Fig. 1 shows that temperatures are lower in rural areas, which are characterized by higher vegetation cover and lower built-up density. Temperatures are higher, especially during the day, in industrial areas, and lower at night. Temperatures then rise in city centers due to population density, which leads to increased energy consumption and increased vehicular traffic emissions, thus contributing to higher air temperatures.

### 3. Description of the Study Area

Baghdad was chosen as a case study to evaluate the spatial analysis of urban heat island developments. The study area extends between latitudes  $32^{\circ}02'24''\text{N}$  and  $33^{\circ}06'00''\text{N}$  and longitudes  $43^{\circ}17'24''\text{E}$  and  $44^{\circ}46'12''\text{E}$ . The summer season in the study area is characterized by a hot and dry climate. The highest temperatures occur in July, ranging between  $42^{\circ}\text{C}$  and  $47^{\circ}\text{C}$ , while the lowest temperatures occur in January, ranging between  $1.5^{\circ}\text{C}$  and  $7.5^{\circ}\text{C}$ . Rainfall patterns show that the highest rainfall occurs in January, ranging between 2.4 and 102.9 mm, while the lowest rainfall occurs in August. Relative humidity levels begin to decrease in the summer reaching their lowest point in July. Humidity levels begin to rise in the winter due to lower temperatures and higher rainfall, reaching their highest point in December (Khudair et al., 2026). The city's terrain varies in elevation between 33 and 41 m above sea level. The highest elevations are located in the western part of Baghdad (Fig. 2).



**Fig.2.** The map of the study area taken from the ASTER (L1B) satellite, which includes the spectral bands (SWIR, red, and green). The Tigris River and the surrounding agricultural lands, open and barren lands, as well as the road network and urban areas can be clearly seen

### 4. Methodology and Data Used

#### 4.1. Data Used

Two satellite images from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) were used to analyse the urban heat island phenomenon in Baghdad. The data were georeferenced to the WGS 1984 UTM Zone 38N projection system. Spring scenes were selected to achieve seasonal homogeneity, with each image representing a decade of the twenty-year study period (2003–2023). Table 1 shows the main characteristics of each scene used.

Spring was selected due to its moderate climatic conditions. This means there are fewer clouds, dust, and smoke in the sky, making it easier to collect surface temperature data from satellite imagery and thus reducing surface temperature measurement errors from imagery. Spring is the growing season of plants, and plants play an important role in cooling the Earth's surface by reflecting solar radiation.

Therefore, choosing spring allows for more reliable assessment of the effect of vegetation on urban heat islands. In winter, plants are dormant or dead, so their effect on surface temperature is less pronounced.

**Table 1.** Technical specifications of ASTER Satellite Scenes used in the study

| Scene No. | Sensor (Band) | Acquisition Date | Acquisition Time (CCT) | Season | Projection System     |
|-----------|---------------|------------------|------------------------|--------|-----------------------|
| 1         | ASTER B1      | March 23, 2003   | 09:38 AM               | Spring | UTM Zone 38N (WGS 84) |
| 2         | ASTER B1      | March 25, 2023   | 10:20 AM               | Spring | UTM Zone 38N (WGS 84) |

## 4.2. Data Preparation

Because satellite images acquired at different times have different atmospheric conditions and viewing geometries, radiometric correction is required. To make these temporal images spectrally similar, a dark object subtraction correction was applied, using special equations included in the ASTER Data User's Manual. The parameters required for input into these equations were the path radiance, the band-specific multiplier rescaling factor, and the band-specific additional rescaling. The values of all these parameters were obtained from the satellite imagery metadata. The digital values of the images used were converted to planetary reflectance for the red and near-infrared spectral bands, using the model provided in the user's manual included with the satellite images.

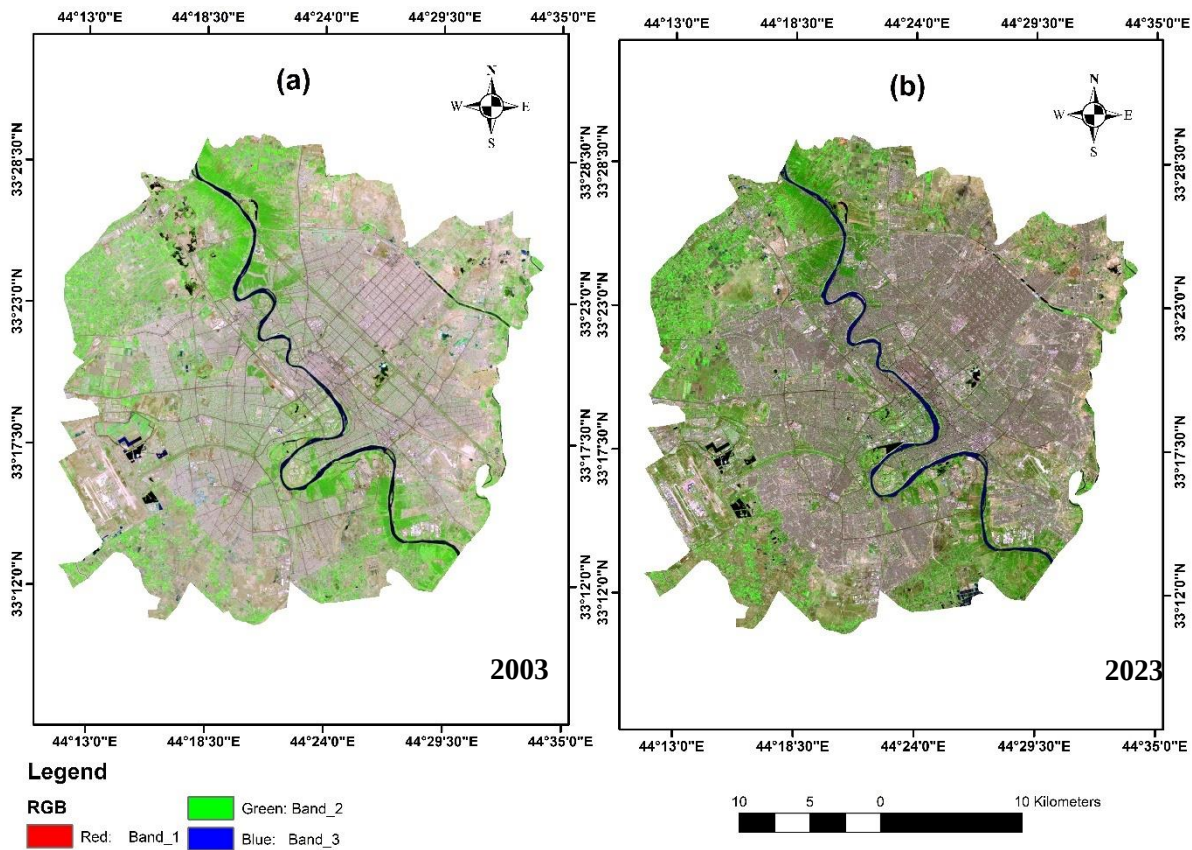
In this process, the model requires the following parameters: (1) minimum and maximum pixel values for quantitative calibration; (2) the spectral radiance scaled to the minimum and maximum pixel values; (3) the Earth-Sun distance; (4) the average solar radiation values outside the atmosphere; and (5) the solar zenith angle. In this case, the required parameters were: (i) the multiplier rescaling factor; (ii) the additional rescaling factor; and (iii) the sun's elevation angle. The correction and atmospheric correction were performed using ERDAS 14.00.0, converting the conversion of digital numbers (DN) to radiance values to facilitate image comparison. The administrative map of Baghdad was corrected and digitized using ArcMap.

The root mean square errors for all corrections were less than 0.5 pixels (15 m). The boundaries of Baghdad and the central city areas were created to define areas of interest (AOIs), which were used as polygons to extract the study area from the entire imagery. Then, spectral bands were stacked from satellite images using ArcMap 10.6 to view the data in color and produce (RGB) images, which helps identify specific phenomena to distinguish and determine the nature of the prevailing land covers. To ensure the correctness of the classification, a number of signatures were collected from the composite band images, where the color combinations RGB = 321 (red band, blue band, and green band from ASTER (L1B), (VNIR, Red, Green) were chosen, as shown in Table 2.

**Table 2.** RGB Band combinations used from ASTER (L1B) for land cover discrimination

| Band No | Spectral Range ( $\mu\text{m}$ ) | Spatial Resolution (m) | Band Description | Usage in Composite  | Typical Assignment |
|---------|----------------------------------|------------------------|------------------|---------------------|--------------------|
| B. 3N   | 0.76 – 0.86                      | 15                     | (VNIR)           | Vegetation analysis | Red                |
| B. 2    | 0.62 – 0.69                      | 15                     | Red              | Surface reflectance | Green              |
| B. 1    | 0.52 – 0.60                      | 15                     | Green            | Water bodies        | Blue               |

Fig. 3 shows the final color images after radiometric calibration atmospheric and geometric corrections for the spectral bands used in Table 2. This helps us improve data quality and enhances image interpretation by calibrating pixel values to obtain reflectance values that represent the true value of the pixel on the Earth's surface.



**Fig. 3.** ASTER RGB Composite images of Baghdad. (a) in 2003, while (b) in 2023. The band combination (RGB = 1, 2, 3N) highlights vegetation in green, built-up areas in grey to dark tones, and water bodies in deep blue

### 4.3. Land Cover Classification

The earth's surface is covered with natural and cultural features; these features are classified into categories called land use and land cover (Bety, 2013). To determine the dominant land cover, Land Use and Land Cover maps (LULC) were prepared using Maximum Likelihood Classification (MLC), an approved land cover classification method provided by ArcMap 10.6, based on selected training samples from the study area. A total of 280 training samples were collected from the three images. The LULC types in the study area were classified into urbanized areas, wastelands, agricultural lands into two types, low density (sparse) and dense finally water bodies (lakes and rivers) listed in Table 3.

The classified land cover maps usually contain some errors due to the classification techniques and image acquisition methods. In order to obtain high-accuracy classification results, 300 random points were selected distributed on the classified maps in areas including urban, urbanized Area, wasteland, agricultural, and water bodies. The accuracy assessment of the land cover classification maps was performed using the producer accuracy and user accuracy method, for all classified land cover classes. The producer accuracy was calculated by dividing the number of correct points in one class by the total number of points derived from the reference image.

The user accuracy was calculated by dividing the number of correctly classified points in each class by the total number of points in the same class. The commission error in the user accuracy was

taken into account, which indicates the probability that a point classified in a certain class represents the same class on the ground, which were implemented using the ERDAS 2014 program.

**Table 3.** Land use and Land cover (LULC) classification legends of the study area and their description

| LULC             | Description                                                                                                                                                                                                                                                                                                                            |
|------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Urbanized Area   | Built-up land, whether residential, commercial, industrial, roads, sidewalks, mixed rural areas, and other urban areas.                                                                                                                                                                                                                |
| Agriculture Land | Agricultural lands of both dense and scattered types, including agricultural crop fields, palm groves, gardens, shrubs, etc., and green areas within urban lands.                                                                                                                                                                      |
| Wasteland        | These are lands that were previously used for any purpose (agricultural, residential, industrial, etc.) but have been abandoned, in addition to barren lands, which do not contain any vegetation cover or are unsuitable for agriculture or agricultural production due to natural conditions such as drought or climatic conditions. |
| Water Bodies     | It includes all natural forms of water on the Earth's surface, such as rivers, lakes, canals, ponds, permanent open water, and reservoirs.                                                                                                                                                                                             |

#### 4.4. Normalized Difference Vegetation Index (NDVI)

It was first deduced in 1973 to provide quick and efficient information about vegetation cover over large areas without the need for a field survey (Becker and Choudhury, 1988). The Normalized Difference Vegetation Index (NDVI) measures the amount and density of green areas in a satellite image (Pettorelli et al., 2011). The spectrum of sunlight consists of multiple wavelengths, some of which are absorbed by the Earth's surfaces, while other wavelengths are reflected. The pigment in plant leaves, chlorophyll, strongly absorbs visible light (from 0.4 to 0.7  $\mu\text{m}$ ) for use in photosynthesis. On the other hand, the cell structure of leaves strongly reflects near-infrared light (from 0.7 to 1.1  $\mu\text{m}$ ) (Huang et al., 2013). Based on this, the NDVI index can be calculated from the visible and infrared bands on a per-pixel basis as the standard difference between the red band and the near-infrared band of the images using the formula (Goward et al., 1991; Pettorelli et al., 2011).

$$NDVI = \frac{(\rho_{NIR} - \rho_{RED})}{(\rho_{NIR} + \rho_{RED})} \quad (1)$$

Where  $\rho_{NIR}$  is the spectral reflectance in the near-infrared band and  $\rho_{RED}$  is the spectral reflectance in the red band.

#### 4.5. Normalized Difference Built-up Index (NDBI)

This is an index used to distinguish urban or densely built-up areas (Dimitriou et al., 2025). The NDBI values depend on the distinct spectral response of built-up areas, which have high reflectivity at mid-infrared wavelengths and lower reflectivity at near-infrared wavelengths (Malik et al., 2019). Therefore, when applied in the study, built-up or urban areas appear white or bright with positive values, while other areas appear dark with negative or zero numerical values (Firozjaei et al., 2019).

$$NDBI = \frac{(\rho_{SWIR} - \rho_{NIR})}{(\rho_{SWIR} + \rho_{NIR})} \quad (2)$$

The  $\rho_{SWIR}$  is the spectral reflectance in the shortwave infrared, and  $\rho_{NIR}$  is the spectral reflectance in the near-infrared.

NDBI calculations for a given pixel always result in a number ranging from (-1) to (+1); Positive values indicate the presence of urban and built-up areas (Bramhe et al., 2018). These areas reflect short-wave infrared radiation. Negative values indicate undeveloped areas such as forests, agricultural lands, and water bodies. These areas reflect near-infrared radiation. Values close to zero indicate areas with an overlap between built-up and unbuilt areas, such as peri-urban areas or areas with some construction such as villages and rural areas (Pattanayak and Diwakar, 2018).

#### 4.6. Land Surface Temperature (LST) Calculation

After obtaining the radiance values corrected from atmospheric factors, The equations for calculating the Earth's surface temperature for emissivity were applied based on the radiation emitted from the Earth's surface according to the following equations (Sekertekin et al., 2020):

$$T_B = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} \quad (3)$$

Where  $T_B$ = brightness temperature at satellite (K) and  $L_\lambda$ =spectral radiance,  $K_1$  and  $K_2$  thermal constant are shown in Table 4.

**Table 4.** Thermal Constants and Variables Used for Land Surface Temperature Calculation from ASTER Data (Hulley et al., 2012)

| Variable    | Description                          | Unit                                            | Value           |
|-------------|--------------------------------------|-------------------------------------------------|-----------------|
| $T_B$       | Brightness temperature at satellite  | Kelvin (K)                                      | Calculated      |
| $L_\lambda$ | Spectral radiance                    | $W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1}$ | Derived from DN |
| $K_1$       | Thermal constant 1 for ASTER Band 13 | Kelvin (K)                                      | 641.27          |
| $K_2$       | Thermal constant 2 for ASTER Band 13 | Kelvin (K)                                      | 1271.22         |

By adopting the NDVI values, thresholds were set in a manner consistent with the presence of vegetation in the image, then linked to the corresponding values of the emission capacity. The selection of the limits of these thresholds is related to the minimum and maximum NDVI values specific to the image and the nature of the land cover. This is done using the values of the normalized differential vegetation index (NDVI) for each pixel (Hulley and Hook, 2010). Therefore, these values must be taken into account in order to set appropriate threshold values for each image. Then, we obtain final images of the corrected surface temperature values according to the final equation 4 (Ayanlade et al., 2021) to calculate the surface temperature in Celsius.

$$S_T = \frac{T_B}{1 + \left(\frac{\lambda \times T_B}{\rho}\right) \times \ln \varepsilon} - 273.15 \quad (4)$$

Where  $S_T$  is land surface temperature in °C,  $\lambda$  is wavelength of emitted radiance in meters (11.5  $\mu m$ ),  $\rho=1.438 \times 10^{-2}$  mK and  $\varepsilon$ =emissivity (ranges from 0.97 to 0.99) that can be calculated from equation Eq. 5 (Yang et al., 2019).

$$\varepsilon = 0.004Pv + 0.986 \quad (5)$$

Where  $Pv$  =proportion of vegetation and it can be calculated by Eq. 6 (Hulley et al., 2012)

$$Pv = \left( \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2 \quad (6)$$

#### 4.7. Statistical Analysis and Pearson's Correlation Coefficient

To better understand the impact of urban expansion on the formation of urban heat islands in Baghdad, it is essential to define the relationship between these factors, their nature, strength, and significance.

A common practice is to apply Pearson's correlation matrix analysis. This matrix incorporates Pearson's bivariate correlation coefficient between pairs of variables (Schober et al., 2018). This coefficient measures the linear relationship between two variables. The type of scale used for the variables determines the type of correlation coefficient. Pearson's correlation coefficient is used with interval or relative scales. Therefore, Pearson's correlation coefficient, which requires two variables, is adopted: the first variable is the independent variable, representing environmental factors such as vegetation cover and urban expansion, and the second variable is the land surface temperature.

Pearson's correlation coefficient is calculated using the following equation: The Pearson correlation coefficient is calculated by the following equation 7 (Okwonu et al., 2020):

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (7)$$

Where  $r$  is Pearson correlation coefficient,  $n$  is sample size,  $x$  values of the independent variables,  $y$  values of the dependent variables with  $i$  (i.e.,  $x_i$  and  $y_i$ ), and  $\sum xy$  is the sum of the product of paired values.

The Pearson correlation coefficient ranges from -1. If it equals one, which is its maximum value, the correlation between the two variables is perfect positive correlation. If it equals -1, it reflects a perfect negative correlation (Wu and Xu, 2010). A correlation coefficient equal to zero indicates that there is no correlation between the two variables, correlation coefficients ranging from 1 - 0.8 or -1 - -0.8 indicate a strong positive correlation in the first case and a strong negative correlation in the second case, finally correlation coefficients ranging from 0.5 - 0.8 or -0.5 - -0.8 indicate medium correlations (De Winter et al., 2016). Correlation relationships ranging from 0.3 - 0.5 or -0.3 - -0.5 are considered weak relationships (Liu et al., 2017).

## 5. Results and Discussion

### 5.1. Analysis of Land Use and Land Cover (LULC) Changes (2003–2023)

Land use and cover were classified using the maximum likelihood method with ArcMap 10.5 software into five main categories Table 3. These categories include urbanized Area, wasteland and water bodies (lakes and rivers). Agricultural land was also classified into two types: low-density and high-density. The classification results showed that the region experienced changes during the period (2003–2023), particularly in urban areas and agricultural land, as shown in Table 5 and Fig. 4, respectively.

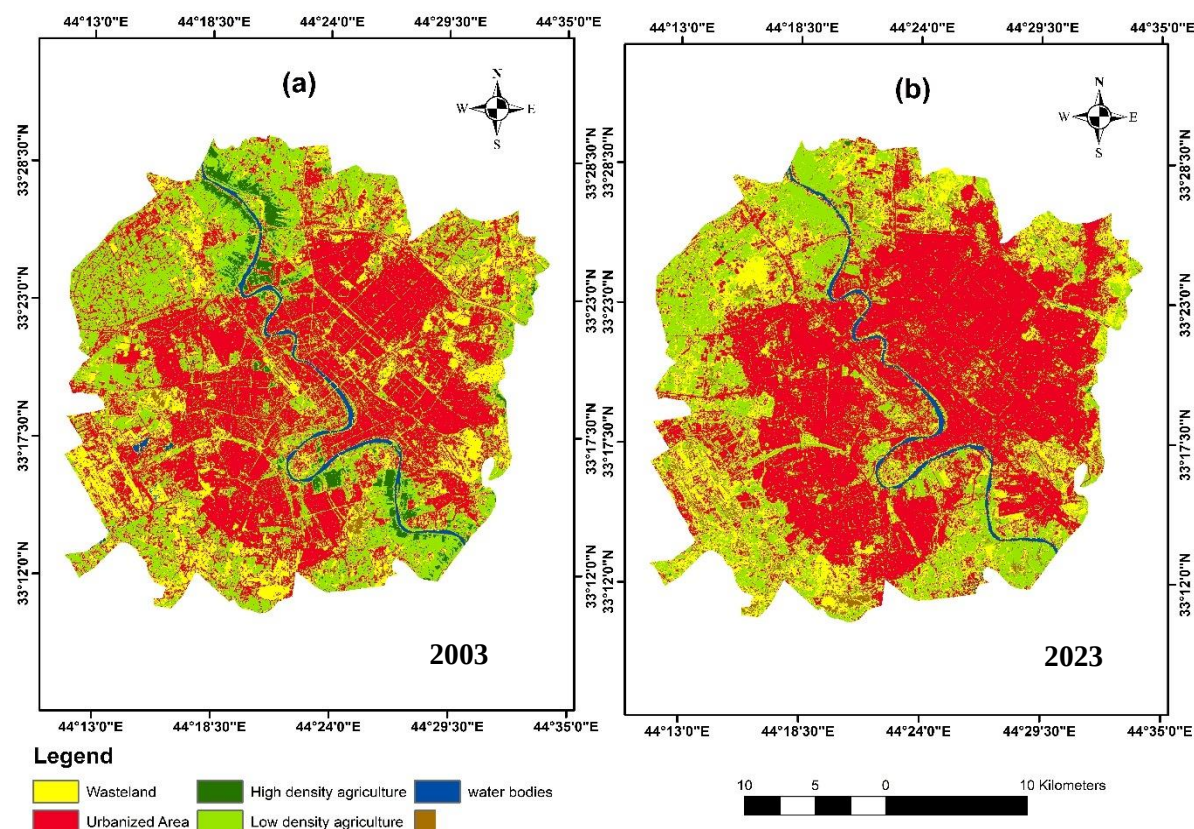
Urbanized area showed a continuous increase in area, rising from 1251.11 km<sup>2</sup> (28.40%) in 2003 to 1548.12 km<sup>2</sup> (35.14%) in 2023, representing an absolute increase of approximately 297.01 km<sup>2</sup> between 2003 and 2023. This indicates a clear urban expansion.

In contrast, high-density agriculture decreased in area from 252.54 km<sup>2</sup> by 5.73% in 2003 to 23.45 km<sup>2</sup>, reflecting a significant shift in agricultural land use to urban land. Low-density agriculture fell from 2126.14 km<sup>2</sup> (48.26%) in 2003 to 1792.41 km<sup>2</sup> (40.68%) in 2023.

The area of wasteland increased from 603.2 km<sup>2</sup> by 13.69% in 2003 to 964.41 km<sup>2</sup> by 21.89% in 2023. As for water bodies, their area fluctuated, decreasing from 116.56 km<sup>2</sup> by 2.65% in 2003 to 68.89 km<sup>2</sup> by 1.56% in 2023, which may reflect the effects of climate change or human activities.

Classified land cover maps usually contain errors for several reasons, the most important of which are the techniques used in classification, in addition to the methods of capturing images and their processing conditions. Therefore, to obtain the most accurate results a comprehensive assessment of accuracy was conducted by calculating the user accuracy and producer accuracy using ERDAS Imagine 2014 software based on the file of reference points that were identified and signed accurately in a random manner and compared with information about the study area.

Table 6 shows the classification accuracy of the images used for the period from 2003 to 2023, In 2003, the product accuracy for urbanized area increased to 92.7% and the user accuracy to 96.3%, while the overall accuracy was 91.41% and the kappa coefficient (capital K) was 0.893. In 2023, the product accuracy for urbanized area increased to 95.5% and the user accuracy to 92.2%, with an overall accuracy of 92.68% and a kappa coefficient of 0.908.



**Fig. 4.** Spatiotemporal Analysis of Land Cover Change in Baghdad City where (a) represents the classified LULC map of Baghdad in 2003, while (b) shows the updated LULC in 2023. The analysis highlights significant expansion in urbanized areas and reduction in agricultural and barren land

**Table 5.** Area in (Km<sup>2</sup>) and percentage (%) of each classified land cover class

| Date      | Urbanized Area  |       | High density agriculture |      | Low density agriculture |       | Wasteland       |       | Water bodies    |      |
|-----------|-----------------|-------|--------------------------|------|-------------------------|-------|-----------------|-------|-----------------|------|
|           | km <sup>2</sup> | %     | km <sup>2</sup>          | %    | km <sup>2</sup>         | %     | km <sup>2</sup> | %     | km <sup>2</sup> | %    |
| 2003/3/23 | 1251.11         | 28.40 | 252.54                   | 5.73 | 2126.14                 | 48.26 | 603.2           | 13.69 | 116.56          | 2.65 |
| 2023/3/25 | 1548.12         | 35.14 | 23.45                    | 0.53 | 1792.41                 | 40.68 | 964.41          | 21.89 | 68.89           | 1.56 |

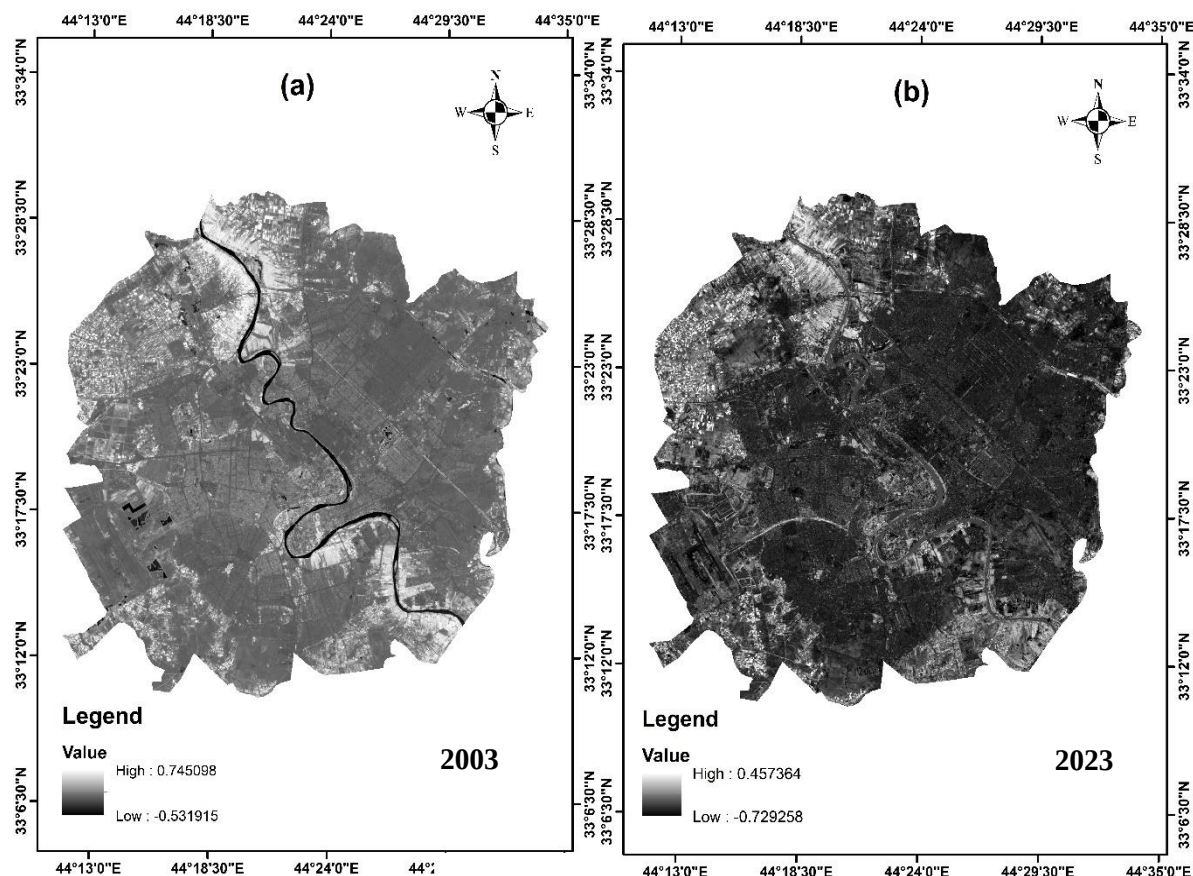
**Table 6.** Statistical analysis of accuracy assessment including user's and product's, the overall accuracy, and the Kappa coefficient for each class of LULC

| LU/LC Categories         | 2003 Accuracy |        | 2023 Accuracy |        |
|--------------------------|---------------|--------|---------------|--------|
|                          | Producer's    | User's | Producer's    | User's |
| Urbanized Area           | 92.7          | 96.3   | 95.5          | 92.2   |
| High density agriculture | 85.4          | 96.7   | 89.87         | 92.6   |
| Low density agriculture  | 89.3          | 92.6   | 90.1          | 92.9   |
| Wasteland                | 96.7          | 81.1   | 91.4          | 93.1   |
| Water bodies             | 83.3          | 100    | 89.1          | 100    |
| Overall accuracy (%)     | 91.41         |        | 92.68         |        |
| Kappa (κ)                | 0.893         |        | 0.908         |        |

## 5.2. Analysis of Spectral Land Cover Indices

### 5.2.1. Normalized Difference Vegetation Index

This index was calculated by implementing the NDVI equation (Equation 1) using ArcMap 10.6 for the Baghdad city during the study period, The NDVI values showed a clear variation in coverage rates over time and according to the Fig. 5 and Table 7, respectively.



**Fig. 5.** Spatiotemporal Variation in NDVI Values in Baghdad (a) shows the NDVI distribution in 2003, while (b) illustrates NDVI for 2023. Higher NDVI values (lighter tones) indicate healthier vegetation cover, while lower or negative values (darker tones) reflect built-up areas, barren land, or water surfaces

Analysis of the NDVI index revealed a decline in vegetation cover in Baghdad over the past twenty years. In 2003, the index reached its lowest value of approximately -0.531 and its highest value of approximately 0.745, indicating significant variation in vegetation cover with high density agriculture.

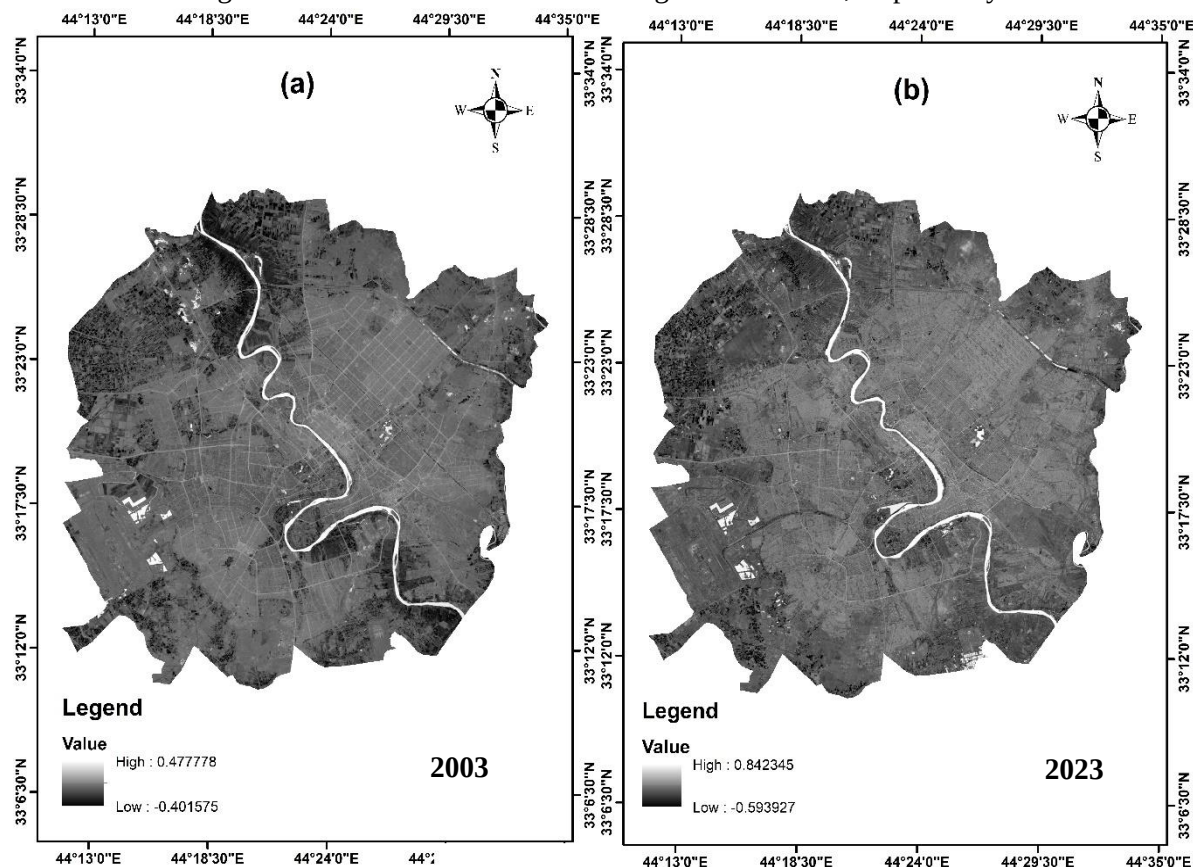
In 2023, both the minimum (-0.729) and maximum (0.457) values decreased significantly, indicating a substantial deterioration in vegetation cover in Baghdad. This period saw a 37.288% decrease in minimum values and a 38.657% decrease in maximum values.

**Table 7.** Trend analysis of NDVI during the period 2003-2023. Positive values indicate an increase, while negative values indicate a decrease

| Date | MIN    | MAX   | MIN Change (%) | MAX Change (%) |
|------|--------|-------|----------------|----------------|
| 2003 | -0.531 | 0.745 | -              | -              |
| 2023 | -0.729 | 0.457 | -37.288        | -38.657        |

### 5.2.2. Normalized difference Built-up Index

The urbanization index was calculated by implementing the NDBI equation (Equation 2) using ArcMap 10.6 for the Baghdad City during the study period, where the NDBI values showed a clear variation in coverage rates over time and as shown in Fig. 6 and Table 8, respectively.



**Fig. 6.** Spatiotemporal Variation in NDBI Values in Baghdad (a) shows the NDBI distribution in 2003, while (b) illustrates NDBI for 2023. Higher NDBI values (brighter tones) indicate dense built-up areas, while lower values (darker tones) correspond to water bodies, vegetation, or non-urban land covers. The spatial expansion of urban surfaces is clearly evident over the two decades

**Table 8.** Trend analysis of NDBI during the period 2003-2023. Positive values indicate an increase, while negative values indicate a decrease

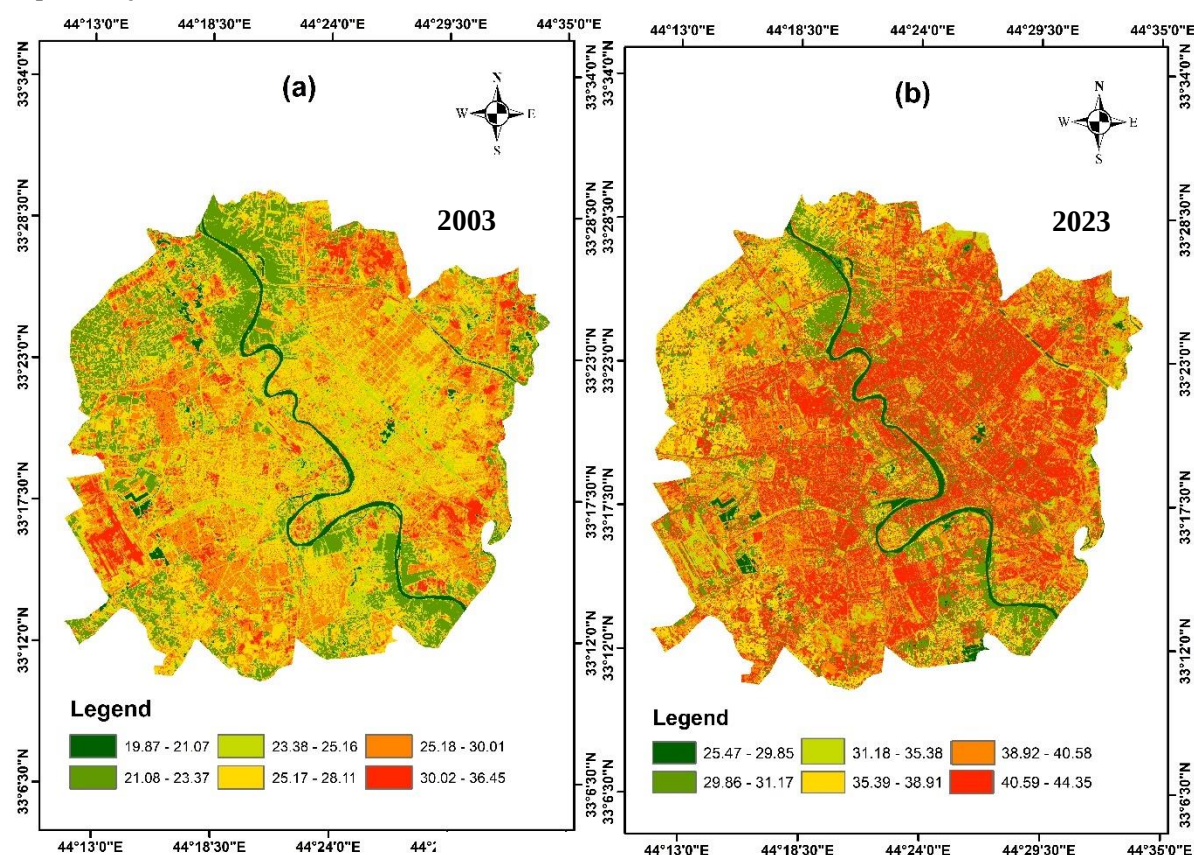
| Date | MIN    | MAX   | MIN Change (%) | MAX Change (%) |
|------|--------|-------|----------------|----------------|
| 2003 | -0.401 | 0.477 | -              | -              |
| 2023 | -0.593 | 0.842 | -47.880        | +66.519        |

The results of the NDBI analysis showed a continuous increase in the area of urban cover in Baghdad over 20 years, and this was observed from Table 5. In 2003, the minimum NDBI value was -0.401, and in 2023, it was -0.593. This represents a decrease of -47.88% from the minimum values, indicating an increase in green spaces or open land in some areas. While in 2003, the maximum NDBI value was 0.477, it rose to 0.842 in 2023. This represents an increase of +66.519%, a clear indication of significant urbanization and infrastructure expansion, as confirmed by the land cover classification.

### 5.3. Spatiotemporal Distribution of Land Surface Temperatures

The LSTs were deduced from the Landsat thermal range and according to the equations (Equations 9-4) in the form of 6 categories classified for the period from 2003 to 2023 based on the maximum and

minimum temperature values of the land surface from regions with low to medium to high temperatures, and these categories are dark green, light green, yellow-green, yellow, orange, and red-orange, in addition to studying the percentage of change for each category according to Fig. 7 and Table 9, respectively.



**Fig. 7.** Spatiotemporal Variation in Land Surface Temperature (LST) Values in Baghdad. (a) shows the LST distribution in 2003, while (b) illustrates LST for 2023. The spatial patterns reveal significant warming in urbanized areas, particularly in the central and southern zones of the city

**Table 9.** Trend analysis of LST during the period 2003-2023

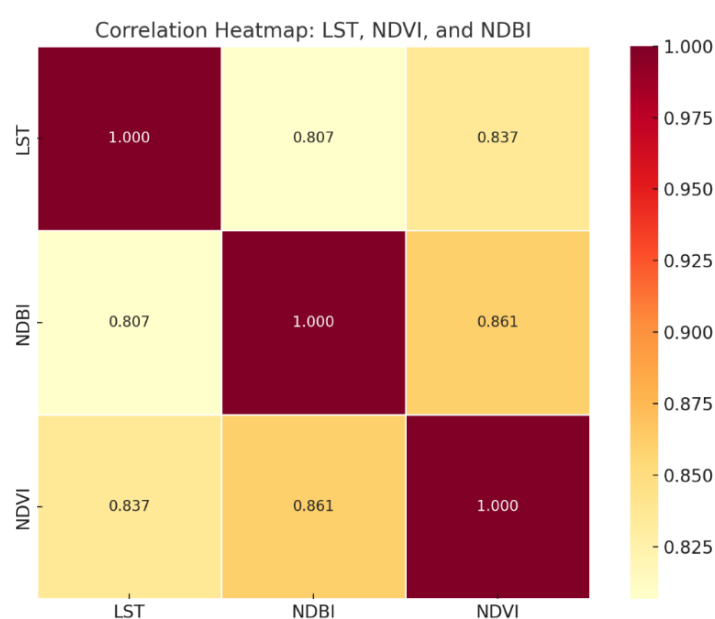
| Class | LST Classification | T <sub>max</sub> | T <sub>min</sub> | T <sub>average</sub> | Mean Increase (2003-2023) | Standard Deviation |
|-------|--------------------|------------------|------------------|----------------------|---------------------------|--------------------|
| 1     | Dark Green         | 27.66            | 19.19            | 22.45                | 8.465°C                   | 2.052              |
| 2     | Light Green        | 30.51            | 21.33            | 24.60                | 9.185°C                   | 2.75               |
| 3     | Yellow-Green       | 33.28            | 23.58            | 26.94                | 9.695°C                   | 3.077              |
| 4     | Yellow             | 37.15            | 25.5             | 29.57                | 11.650°C                  | 3.753              |
| 5     | Orange             | 39.75            | 27.33            | 31.62                | 12.415°C                  | 3.841              |
| 6     | Red-Orange         | 42.47            | 31.45            | 35.92                | 11.015°C                  | 2.105              |

The study period witnessed a significant increase in surface temperature from 2003 to 2023, with the average increase in surface temperatures in the "orange" category reaching 12.415°C, while the "dark green" category experienced the least increase, with an average of 8.465°C. Temperature change shows that the "orange" and "yellow" categories had the highest standard deviation, indicating that temperatures in these two categories were more variable over the time period, while the "dark green" and "orange-red" categories recorded the lowest standard deviation, indicating relative stability in temperature across time periods. Maximum temperatures also increased, from 34.55°C in 2003 to

44.35°C in 2023. The trend continued upward, with the highest average temperatures in 2023, ranging from 25.47°C to 44.35°C. The temperature increase was most pronounced in the "orange" category, averaging 4.215°C. Between 2003 and 2023, the temperature increase ranged from 5.15°C to 8.16°C. Over 20 years, the "yellow" category had the largest overall increase, averaging 11.65°C. Other categories experienced increases ranging from 8.465°C to 11.015°C. The graph shows a clear increase in average temperatures for all categories. The "yellow" "orange," and "red-orange" categories had the largest increases. High Land Surface Temperature (LST) are concentrated in all densely populated urban areas, industrial areas, and arid regions.

#### 5.4. Analysis of the Correlation Between NDVI and NDBI with LST

The correlation matrix between ground surface temperature (LST), the built-up area index (NDBI), and the vegetation cover index (NDVI) was calculated using ASTER satellite data from 2003 and 2023, as shown in Fig. 8.



**Fig. 8.** Correlation matrix between NDVI and NDBI variables with LST

The results showed that the correlation coefficient between LST and NDVI was 0.837, indicating a strong positive relationship between rising surface temperature and decreasing vegetation density. The correlation between LST and NDBI was approximately 0.807, demonstrating that urban expansion and the increase in built-up areas contribute significantly to rising surface temperatures. Urban heat increases as a result of the urban heat island phenomenon. Urban expansion leads to environmental thermal imbalances, and the strong correlation between NDBI and NDVI, which reached 0.861, reflects the accelerated land-use shift from green areas to built-up areas, a clear characteristic of urban expansion in Baghdad over the past two decades. Taken together, these results indicate that urban heat islands in Baghdad are closely linked to urban expansion and vegetation degradation.

#### 6. Conclusions

This study aimed to perform a spatial analysis of the urban heat island effect resulting from urban expansion in Baghdad, using remote sensing techniques. ASTER satellite imagery was used to represent remote sensing data from spring 2003 to 2023. According to the data reviewed and analyzed in this study, the average surface temperature of Baghdad increased significantly over a twenty-year period.

This increase is caused by multiple interacting factors, most notably environmental factors and global climate change. The environmental factors studied included an assessment of the impact of urban and vegetation cover. The analysis revealed substantial changes in the areas and proportions of land cover categories over a twenty-year period.

The central and northern areas of the city have witnessed significant expansion of built-up areas, with bare land replacing most of the natural vegetation. This urban sprawl has altered the radiative properties of the Earth's surface, causing an imbalance in surface energy and consequently increasing surface temperature. The spatial distribution of maximum and average temperatures showed increases of 4.92°C and 7.13°C, respectively, during the study period, while the change in minimum temperatures was negligible.

On the other hand, agriculture, both in terms of density and dispersion, has seen a significant reduction in agricultural land area. Where the agricultural areas of Taji, Rashid, and Al-Baitha exhibited lower surface temperatures compared to the Baghdad Al-Jadeeda, Al-Amiriya, and Baghdad Airport stations, all located within the Baghdad metropolitan area. When vegetation density is low, surface temperatures rise because there is insufficient vegetation to absorb sunlight, leading to increased surface temperatures.

#### **Author contributions: CRediT**

Khaleel Ibrahim Abood, Shahad Mohamed Ahmed and Abdulrahman Bilal Ali conceived the overall framework for the study. Khaleel provided resources, supervised the work, managed the project, and reviewed and edited the manuscript. Abdulrahman developed the methodology, presented it visually, wrote the original draft, and validated the results. Shahad performed the software processing, spectral analysis, and data formatting.

#### **Declaration of Competing Interest**

The authors declare that they have no competing financial interests or personal relationships that could influence the work reported in this study.

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#### **Data Availability**

The data that support the findings of this study are openly available in USGS EarthExplorer at <https://earthexplorer.usgs.gov/>

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