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MONTHLY SURFACE WATER TEMPERATURE VARIATION AT AL-HINDIYAH BARRAGE, IRAQ, MEASURED USING THE REMOTE SENSING TECHNIQUE

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ABSTRACT

Aim of the study
The research problem of this study is to model and track the surface water temperature changes in the Euphrates River at Al-Hindiyah Barrage, Iraq, by relying on in situ measurements and Landsat 8 and 9 satellite (2018–2024).

Material and methods
This study employed GIS and statistical methods to process field observations, and Landsat satellite thermal infrared images to determine average monthly surface water temperatures. The Landsat dataset had about 4.8% missing data points, while on-site measurements had approximately 1.2% missing values. Missing data were reconstructed using IBM SPSS Statistics (Version 26) through mean compensation, substituting missing values with the arithmetic mean of the same month across the available years. This approach ensured a stable and reliable time series, enabling us to model the relationship between on-site and satellite-measured temperatures via simple linear regression. Linear regression performance at Al-Hindiyah Barrage was assessed using the Nash–Sutcliffe efficiency coefficient.

Results and conclusions
Results show that in situ water temperatures produced significant monthly temperature variation (actual water temperatures ranged from a minimum of 11.8°C to a maximum of 32.9°C), whereas satellite data recorded an even wider temperature spread, ranging from a minimum of 12.0°C to a maximum of 40.8°C. A highly significant correlation ($R^2 = 0.93$) between datasets shows that in the case of Landsat-derived water temperature values, NSE reached 0.89, thus indicating excellent agreement between the observed and the estimated values. These findings validate Landsat for monitoring water temperature, supporting water resource management and ecosystem protection. Integrating remote sensing with traditional methods enhances assessment accuracy for environmental decision-making and adaptation. The low-cost predictive linear regression aids monitoring in data-scarce and arid areas.

Keywords: surface water temperature, SPSS, Landsat 8 and 9, Al-Hindiyah Barrage

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HIGHLIGHTS

- Euphrates temperatures: in situ 11.8°C–32.9°C; Landsat 12.0–40.8°C (2018–2024);
- strong correlation: R^2 = 0.93R^2 = 0.93R^2 = 0.93, NSE = 0.89;
- Landsat: reliable for data-sparse water monitoring;
- low-cost linear regression aids climate-adaptive resource management.

INTRODUCTION

Increasing air temperatures, together with water allocation challenges of a more complex nature and the decline of instream habitats, affect many dryland areas. Water temperature reflects a basic physical property of aquatic ecosystems, which affects many water quality parameters related to domestic hydrological, environmental, industrial, and agricultural aspects. Increasing the temperature of water decreases solubility of gases while increasing solubility of minerals, changing the chemical composition of the aqueous environment. Moreover, high temperatures increase chemical and biological reaction rates, enhance the toxicity of pollutants, and affect water treatment performance as well as taste and odor characteristics. More than just physicochemical implications, water temperature affects physiological functions, reproduction, and the distribution of many aquatic organisms (Liu et al., 2020; Mohseni et al., 2003; van Vliet et al., 2011). Thermal conditions dictate the growth, respiration, and competitive interactions of most aquatic organisms, and specific temperature tolerance thresholds of species likely play a critical role in their survival and reproduction. Furthermore, temperature also plays an important role in providing industrial and agricultural water needs. Nonetheless, the sustainable heat provision necessary to satisfy thermal needs for these sectors as well as ecological and environmental demands is still a major challenge. Reservoir operations and release-structure configurations directly affect downstream thermal regimes, often creating difficult trade-offs. Cold water conditions are vital to the survival of anadromous fish species, but some types of agricultural use (such as irrigation of specific crops) can tolerate (or even require) warm water temperatures in the initial steps of seed germination.

In addition to these operational challenges, the potential changes of the thermal regime of aquatic systems has been a growing concern over the last few years. Rising global temperatures may significantly alter hydrological patterns and thermal regimes, with far-reaching consequences for water resources planning, infrastructure design, reservoir operations, and long-term management strategies (Deas and Lowney, 2000).

An increasing temperature has consistently characterised Iraq, and this particular condition has a paramount effect on both the quality and availability of the surface water resources (Al-Ansari, 2013; Muhammed and Al-Dabbas, 2022). Iraq, similar to other arid regions, is experiencing elevated temperature levels, and scientists assert with high confidence that global temperatures will continue to rise in the coming years and decades. This projected increase is primarily attributed to greenhouse gases emitted as a result of human activities (Al-Ali and Al-Dabbas, 2021). Accurate understanding and monitoring of spatial and temporal patterns of water temperature are essential for understanding the health of riverine ecosystems, addressing and managing water resources in a sound scientific manner (Wang et al., 2025). Temperature changes, along with changes in net radiation, wind speed, and air humidity, are major factors that cause changes in evaporation patterns (Rong et al., 2013). The lowest value of the latter was recorded in 2003, and the highest, in 2018 (Seif et al., 2023).

The Euphrates River plays a pivotal role in sustaining aquatic ecosystems, functioning as the primary conduit for ecological processes and simultaneously acting as a major transporter and potential source of pollutants within freshwater environments (Hussein et al., 2023). The Lower Euphrates River Basin, which lies predominantly within the territory of Iraq, is highly susceptible to various impacts. As an example, the change in temperature and various precipitation patterns have direct effects on the amount and quality of runoff on the surface, besides having some impact on evapotranspiration rates. Therefore, any increase in water temperature will have significant implications for irrigation systems, hydro-power generation, and water availability, as well as contributing to the decline of the available water resources in the arid zones surrounding Iraq owing to the construction of numerous dams on the river (Al-Abbawy, n.d.; Imteaz et al., 2017).

One of the key sources of livelihoods in central and southern Iraq is the Euphrates River, which is one of the most significant transboundary rivers in the Middle East. The Euphrates provides agricultural irrigation, domestic water, hydroelectric generation, and sustainability of the environment. Nevertheless, the large-scale dam constructions and the rise in water abstractions have dramatically changed the river's hydrological and thermal cycles, turning into a challenge of water supply, both in terms of its quantity and quality. The Al-Hindiya Barrage is a major hydraulic facility in the Babil Governorate. The barrage controls the flow of water in the Euphrates and allocates it to various governorates, which include Babylon, Karbala, Al-Najaf Al-Ashraf, Al-Muthanna, Al-Qadisiyah, and Thi-Qar. Since the aforementioned facility is situated in a strategic place in terms of water allocation and agricultural productivity, it is vital to know and observe surface water temperature in this location.

Conventional in situ measurements are useful in terms of providing dependable temperature readings, but they tend to be limited in terms of the distance they can travel, the difficulty of accessing the information, and the number of data gaps in the information. In the past few decades, satellite-based remote sensing has emerged as a powerful tool for mass and continuous measurements of water temperature. It offers total space and time coverage. Thermal infrared bands in the Landsat 8 and 9 missions with a medium spatial resolution have proved invaluable in predicting land and surface water temperatures by means of enhanced retrieval. Temperature data collected by satellites could be a valuable supplement or even a substitute for ground-based observations, particularly in those areas where field data are difficult to obtain or where they are not exhaustive when used in conjunction with Geographic Information Systems (GIS) and statistical modeling.

Our objective in this paper was to combine field-measured (real-world) water temperature data on Al-Hindiyah Barrage with temperature estimates from satellite imagery of Landsat 8 and 9 data in 2018 and 2024. Whereas there are field measurements of the Al-Hindiyah Barrage available, there is a spatial and temporal gap in knowledge of the thermal dynamics of the Euphrates River. In addition, there exist no sufficient research findings on the reliability of satellite-derived data in the long run in Iraq. The proposal was to address this gap by integrating real data on water temperatures with temperature data estimated using Landsat 8 and 9 images over the years 2018 to 2024. To examine the statistical correlation between the two sets of data, we adopted a simple linear regression model. The Nash–Sutcliffe efficiency coefficient (NSE) was used to assess the performance of the model, and the difference between the observed NSE and the estimated NSE was high. The model aimed to create a way through which remote sensing data could be used in forecasting real water temperatures. This paper will enhance the accuracy and reliability of monitoring the Euphrates River temperature at the Al-Hindiyah Barrage, which will benefit improved civil and environmental engineering, water resource management, and climate change preparedness. Landsat water temperature monitoring assist in the monitoring of surface water temperature changes in the Al-Hindiya Barrage, which can be a valuable way of filling the gap in the local body of knowledge on water resource management and ecosystem protection, and facilitate informed decision-making and adaptation planning of the important infrastructure.

Past research in Iraq and the neighboring areas has primarily dealt with parameters of hydrology and water quality, including river discharge, pH, total dissolved solids (TDS), and electrical conductivity. Nevertheless, the literature related to water temperature is quite scarce, although this parameter plays a crucial role in controlling physical, chemical, and biological processes occurring in the river and reservoir systems.

Specifically, none of the past studies has examined water temperature at the Al-Hindiyah Barrage applying remote sensing data obtained with a satellite and confirmed with the measured in situ values. Thus, the paper presents a pioneering, initial effort to evaluate and confirm temperatures by combining surface water and ground-based observations with Landsat 8 and 9 thermal products at the Al-Hindiyah Barrage. This constitutes a critical local research event, while offering a generalizable approach to methodology in comparable regulated river systems in arid areas.

STUDY AREA

The Al-Hindiyah Barrage is one of Iraq's most essential hydraulic infrastructure projects, acting as the main control center for management and distribution of Euphrates River water to the center and south parts of Iraq. Water is conveyed through the main course of the Euphrates River and an intricate network of upstream lateral canals, including the Musayyib Canal, Shatt Al-Hillah, Kifil Canal, Beni Hassan Canal, and Al-Hussainiyah Canal, ensuring effective distribution for agricultural, domestic, and environmental purposes (Al-Sultani and Al-Hadidi, 2023). The Al-Hindiyah Barrage facilitates the flow of water from the Al-Hillah River and the Al-Hindiyah River during the summer season. The new Al-Hindiyah Barrage is located approximately 1.700 km upstream from the old Al-Hindiyah Barrage, providing irrigation to 500,000 hectares of agricultural land. This includes 420,000 hectares in the Shat Al-Hillah area, 25,000 hectares in the Kifil Canal, 30,000 hectares in the Bani Hassan Canal, and 25,000 hectares in the Hussainiyah Canal (Hassan Hommadi et al., 2018). The Saddat Al-Hindiyah region encompasses an estimated area of 202.08 km^2, forming a strategically significant zone for hydrological studies and water resource management within the central and southern parts of Iraq. The geographical boundaries of the study area are defined by latitudinal coordinates ranging from 32°40′14″N to 32°47′24″N and longitudinal coordinates extending from 44°11′53″E to 44°21′48″E, delineating a precisely mapped region, which is essential for hydrological and environmental analyses. Therefore, a precisely defined area necessary for hydrological and environmental analyses has been established. The 32°43'43.3"N 44°16'12.3"E point represents the location for taking readings at the rear of the Shat Al-Hillah regulator, left side as shown in Figure 1.

DATA

Actual water temperature

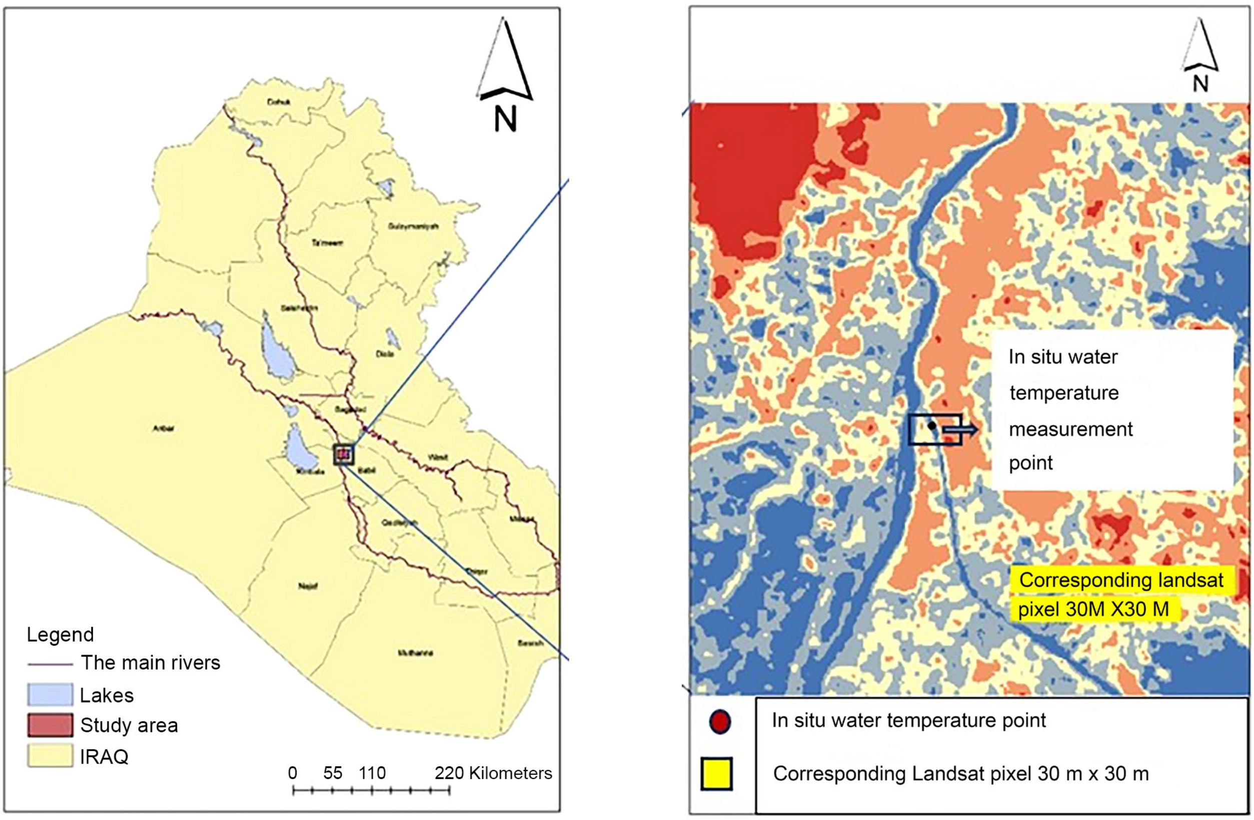
Real water temperature data were collected at the Al-Hindiyah Barrage Project on the Euphrates River in Babil Governorate, Iraq. These values were measured at the top of the water surface. The data were collected monthly with the help of field monitoring systems. The dataset spans 2018–2024, creating a complete time series that allows for the examination of thermal changes in the river water and the identification of any suspicious temperature variations in the study area.

Satellite (Landsat) water temperature

This study utilized multispectral remote sensing images of the Landsat 8 and 9 satellites to track the surface water temperature in the Al-Hindiyah Barrage every month. The dataset covers the period from 2018 to 2024. The spectral band descriptions for Landsat 8 and 9 are available on the official website of the United States Geological Survey (USGS) (http://www.usgs.gov). Level 2 Science Products (Level 2-SP) were used, available within the Landsat Collection 2 archive (https://www.usgs.gov/landsat-missions/landsat-collection-2-level-2-science-products). The satellite imagery covered the Al-Hindiyah Barrage area during daytime, corresponding to Path/Row 168/37 and 169/37. All data were downloaded from the USGS website at a spatial resolution of 30 meters. The data were reprojected to the Universal Transverse Mercator (UTM) coordinate system, WGS84 datum, Zone 38 North. Data analysis was conducted using ArcGIS software (ArcMap), version 10.8.

Table 1 provides a reference for the spectral bands of Landsat 8 and 9 used in this study for water temperature analysis. The United States Geological Survey (USGS) has processed all archived Landsat 8 and 9 (Operational Land Imaging, OLI), and TIRS thermal infrared sensor data, converting them into Analysis Ready (ARD) data. This ARD data significantly reduces the pre-processing burden on Landsat data users. The availability of ARD data is intended to facilitate the production of land cover maps and comparative maps, as well as other derived geophysical and biophysical products, using Landsat data. ARD data is presented as segmented, geo-recorded, elevation-corrected, and iso-area projection maps, accompanied by clear spatial quality assessment information and appropriate metadata to enable further processing while maintaining data source traceability (Dwyer et al., 2018; Wachmann et al., 2024).

(a) Illustrative Google map for Al-Hindiyah Barrage



(b) Map of Iraq (c) showing the study area from Arc Gis

Fig. 1. Location of Al-Hindiyah Barrage: (a) Google Map, (b) Iraq map, and (c) study area extracted from ArcGIS showing the in situ water temperature measurement point (Source: Authors' own elaboration)

Table 1. Landsat 8 and 9 band reference (Landsat 8 and 9 Operational Land Imager (OLI)-Thermal Infrared Sensor (TIRS) Collection 2 (C2) Level 2 (L2) Data Format Control Book (DFCB), 2022)

Band reference number	Band description	Band range [nm]
1	Coastal Aerosol (Operational Land Imager (OLI))	435–451
2	Blue (OLI)	452–512
3	Green (OLI)	533–590
4	Red (OLI)	636–673
5	Near-Infrared (NIR) (OLI)	851–879
6	Short Wavelength Infrared (SWIR) 1 (OLI)	1566–1651
7	SWIR 2 (OLI)	2107–2294
10	Thermal Infrared Sensor (TIRS) 1	10,600–11,190

METHODOLOGY

Remote sensing images from Landsat 8–9 satellite were acquired between 2018 and 2024, and subsequently downloaded from the USGS Earth Explorer (http://www.usgs.gov) with a spatial resolution of 30 meters. Descriptions of Landsat 8–9 bands are available, and the images were used with Collection 2 Level 2 science products (https://www.usgs.gov/landsat-missions/landsat-collection-2-level-2-science-products). All images covered the study area corresponding to Path/Row 168/37 and 169/37. The data were reprojected into the Universal Transverse Mercator (UTM) coordinate system, reference WGS84, zone 38N. All Landsat data were processed by the USGS. Enhanced Landsat 8 (Operational Land Imager, OLI), and archived TIRS thermal infrared sensor data were converted into analysis-ready (ARD) data. This ARD data significantly reduces the pre-processing burden on Landsat data users. The provision of ARD data aims to facilitate the production of land cover and change maps, as well as other derived geophysical and biophysical products, using Landsat data. ARD data are presented as segmented, geo-recorded, elevation-corrected, and equal-area projection maps, accompanied by clear information for spatial quality assessment and appropriate metadata to enable further processing while maintaining data source traceability. Table 1 shows the spectral characteristics of the Landsat 8 and 9 (OLI/TIRS) beams used in water temperature analysis. The Analysis Ready Data (ARD) Surface Temperature (ST) products were generated using a single-channel algorithm, originally developed by Cook et al. and subsequently refined by Malakar et al. This algorithm was applied to the Thermal Infrared Sensor (TIRS) Band 10 (Wachmann et al., 2024) (10,600–11,190 nm), as summarized in Tables 1 and 2, as part of the Landsat Level-2 Surface Temperature processing framework.

Surface temperature data are available globally from the Landsat series of satellites in the following chronological order: Landsat-8 OLI (2013–present), and Landsat-9 OLI-2 (2022–present).

The selected Landsat images provided surface temperature values in Kelvin, obtained through the application of Landsat-defined radiometric conversion coefficients.

$$K = \text{DN-ST-B} \times 0.00341802 + 149 \tag{1}$$

where:

K – the land surface temperature expressed in Kelvin,

DN-ST-B – the digital number-surface temperature-band (band 10 for Landsat 8 and 9).

Subsequently, the temperature values were converted from Kelvin to Celsius degrees using the standard transformation (Wachmann et al., 2024).

$$°C = K - 273.15 \tag{2}$$

where:

°C – the surface temperature expressed in degrees Celsius.

Surface water temperature data, specifically the monthly maximum and minimum values, were obtained from satellite imagery (Landsat) for the period between 2018 and 2024, using Geographic Information Systems (GIS). These data are summarized in two separate tables: Table 3 presents the minimum monthly water temperatures, while Table 4 shows the maximum monthly water temperatures for the same period. These datasets contained missing values, which were identified and addressed using statistical imputation techniques in IBM SPSS Statistics (Version 26). Specifically, the Transform → Replace Missing Values procedure with the series mean imputation method was applied, whereby each missing value was replaced by the arithmetic mean of the corresponding month across the available years, in order to preserve the integrity and temporal consistency of the time series. The distribution of missing values for the minimum monthly water temperatures is detailed in Table 5, while the missing values for the maximum monthly water temperatures are presented in Table 6. Subsequently, the monthly maximum and minimum values were used to produce the monthly average surface water temperatures derived from satellite data. These calculated averages, expressed in degrees Celsius [°C], are presented in Table 7.

Monthly actual surface water temperatures were collected from the Al-Hindiyah Barrage site for the same time period (2018–2024). The actual monthly data collected from the Al-Hindiyah Barrage included some missing values, which were estimated using IBM SPSS Statistics (Version 26) through Transform → Replace Missing Values with the series mean imputation method as part of the data pre-processing stage. Subsequently, the data were processed to obtain the actual monthly average water temperatures using a PivotTable in Microsoft Excel. Table 8 presents the calculated monthly average actual surface water temperatures for the Al-Hindiyah Barrage site during the study period. It should be noted that some months contained only one or two field measurements, making median calculation unreliable for these periods. Therefore, the arithmetic mean was consistently used to summarize monthly field water temperatures. Similarly, satellite-derived monthly temperatures (Landsat 8 and 9) were obtained by averaging the monthly maximum and minimum values. Using the mean consistently across both datasets ensures comparability between field and satellite measurements, while acknowledging the potential influence of extreme values. A single missing value was identified in the actual monthly average water temperature dataset for April 2020, and it was estimated using SPSS software. Table 9 summarizes the identification and treatment of the missing value within the actual monthly average water temperature dataset.

After preparing the two datasets − that is, (1) the monthly average water surface temperatures derived from satellite imagery, and (2) the monthly average actual water temperatures from the Al-Hindiyah Barrage − a Simple Linear Regression analysis was performed to evaluate the statistical relationship between the two time series. The analysis yielded the following regression equation:

$$Y = 1.3246X - 2.1929$$

where:

- Y − the monthly average actual water temperature measured in situ [°C],
- X − the monthly average water temperature derived from Landsat imagery [°C].

The regression model achieved a coefficient of determination (R^2) of 0.93, indicating that 93% of the variance in average monthly actual water temperatures can be explained using Landsat data. The purpose of this analysis was to create a predictive model that would be able to forecast the actual water temperatures with the help of remotely sensed data, which in turn could make the process of water resource monitoring more efficient and enable making well-informed decisions in the field of civil and environmental engineering.

In order to measure the performance of the statistical linear regression and check whether it is predictive or not, another measure, the Nash–Sutcliffe Efficiency Coefficient (NSE), was employed to determine the quality of the agreement between the observed and the estimated values. A common indicator in hydrological and environmental research, the NSE takes a value of 0.75 and above, indicating very good predictive efficiency, and a value below 0.75, indicating good predictive efficiency, meaning that values near 1 indicate high model performance. The equation to compute the NSE coefficient is given below:

$$NSE = 1 - \sum I = \ln(OBSi - OBS)$$
$$2 \sum I = \ln(OBSi - SIMi)_2$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} \left(OBS_i - SIM_i\right)^2}{\sum_{i=1}^{n} \left(OBS_i - \overline{OBS}\right)^2}$$

where:

OBS_i – the observed water temperature values (field-measured in situ),
SIM_i – the estimated or calculated values using the regression model,
OBS – the arithmetic mean of the observed values,
n – the total number of observations.

The results of the analysis revealed that the NSE value of the mean temperature of the surface water in a month that was extracted using satellite images and the actual temperature of the water in the Al-Hindiyah Barrage site was 0.89, indicating a high predictive power of the model that was adopted and a high agreement of the model. Based on the time-series data of water temperature sampled at the geo-located Landsat pixel at the known point of Al-Hindiyah Barrage (Fig. 1), the Nash–Sutcliffe Efficiency (NSE) was determined. The derived NSE value (0.89), as shown in Figure 3, is thus the model response in the mapped study area as well as the proximate river reach at the barrage. The NSE value thus validates the model's application in water resource compliance and decisions in the engineering of civil and environmental sciences.

Table 2. TIRS ST band

Identifier FT	Units	Range	Fill Value
ST_B10	Scaled Kelvin	1 through 65535	0 (No Data)

Table 3. Minimum monthly water temperatures [°C] derived from Landsat imagery using ArcGIS

Years	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2018	11.3		20.5	26.8		30.6	35.1	32.9	34.7	19	16.7	13.9
2019	9.3	15.8	18.4	22.9	32.6	34.2	31.9	32.8	31.6	28.2	20.5	
2020	13.4	13.2	18.1	10.5	28	32.8	34.5	33	32.3	26.9	18.9	13.9
2021	11.7	17.6	9.1	22.3	31.6	34.1	34.9	35.4	32.1	24.9	17.3	13.5
2022	14.1	15.6	17.3	22.9	27.9	35	30.2		33.9	26.9	21.3	11.9
2023	12.1	12.9	20.3	26.1	30.5	33.4	31.6	35.8	31.4	27	21.2	16.5
2024	15.1	14.7	18.8	26.6	32.4	33.6	35	34.3	31.1	27.7	20.6	13.7

Table 4. Maximum monthly water temperatures [°C] derived from Landsat imagery using ArcGIS

Years	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2018	16.1		25.9	33.7		37.5	43.9	40.9	41.8	20.7	20.7	16.6
2019	14.3	20.1	23.4	29.5	40.7	43.2	41.3	41.3	38.8	34.3	24.1	
2020	16.8	16.3	23	23.1	35.7	42.9	43.5	40.2	39.4	31.9	22.5	17
2021	14.9	21.9	25.5	27.5	40.5	43.4	43.8	43.8	38.9	31.9	21.7	16.8
2022	17.6	20.4	22.9	29.1	35.2	40.9	37.3		40.9	32.9	25.8	15.1
2023	14.5	16.5	24.5	32.5	38	41.4	40.9	45.8	38.9	33.2	24.2	20.5
2024	18.6	19.6	23.3	36.4	40.3	44.1	45.4	44.6	39.4	35.1	24.7	17.3

Table 5. Missing values analysis for minimum monthly water temperatures [°C] using SPSS

Years	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2018	11.3	12.3	20.5	26.8	27.7	30.6	35.1	32.9	34.7	19	16.7	13.9
2019	9.3	15.8	18.4	22.9	32.6	34.2	31.9	32.8	31.6	28.2	20.5	12.3
2020	13.4	13.2	18.1	10.5	28	32.8	34.5	33	32.3	26.9	18.9	13.9
2021	11.7	17.6	9.1	22.3	31.6	34.1	34.9	35.4	32.1	24.9	17.3	13.5
2022	14.1	15.6	17.3	22.9	27.9	35	30.2	31.3	33.9	26.9	21.3	11.9
2023	12.1	12.9	20.3	26.1	30.5	33.4	31.6	35.8	31.4	27	21.2	16.5
2024	15.1	14.7	18.8	26.6	32.4	33.6	35	34.3	31.1	27.7	20.6	13.7

Table 6. Missing values for maximum monthly water temperatures [°C] using SPSS

Years	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2018	16.1	16.8	25.9	33.7	36.1	37.5	43.9	40.9	41.8	20.7	20.7	16.6
2019	14.3	20.1	23.4	29.5	40.7	43.2	41.3	41.3	38.8	34.3	24.1	14.6
2020	16.8	16.3	23	23.1	35.7	42.9	43.5	40.2	39.4	31.9	22.5	17
2021	14.9	21.9	25.5	27.5	40.5	43.4	43.8	43.8	38.9	31.9	21.7	16.8
2022	17.6	20.4	22.9	29.1	35.2	40.9	37.3	39.1	40.9	32.9	25.8	15.1
2023	14.5	16.5	24.5	32.5	38	41.4	40.9	45.8	38.9	33.2	24.2	20.5
2024	18.6	19.6	23.3	36.4	40.3	44.1	45.4	44.6	39.4	35.1	24.7	17.3

Table 7. Landsat average monthly water temperatures [°C] from Landsat data

Years	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2018	14	14.6	23.2	30.3	32	33.4	40	37	38.3	19.9	19	15.3
2019	12	18	21	26.2	36.7	38.7	36.7	37.1	35.2	31.3	22.3	13.5
2020	15.1	14.8	20.6	17	31.9	37.9	39	37	35.9	29.4	21	15.5
2021	13.3	19.8	17.3	25	36.1	38.8	39.4	39.6	36	28.4	20	15.17
2022	15.9	18	20.1	26	31.6	38	33.8	35.2	37.4	30	23.6	14
2023	13.3	15	22.4	29.3	34.3	37.4	36.3	40.8	35.2	30.1	23	19
2024	16.9	17.2	21.1	32	36.4	38.9	40.2	39.5	35.3	31.4	23	16

Table 8. Actual average monthly water temperatures [°C]

Years	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2018	15.7	16.3	20	22.6	26.9	32.9	31.6	30.8	31.2	26.5	19.8	16.1
2019	13.8	14.9	16.4	21.2	25.9	30.5	29.9	29.6	27.7	25	25	20.9
2020	13.3	14.6	18.5		25	28.3	32	30	30.3	26	19.8	14.5
2021	12.5	14.9	17.5	21.7	26.7	28.4	31.2	31.5	25.3	21.1	18.8	15.2
2022	11.8	13.4	15.5	22.1	25.9	29.9	32.1	31.1	30.2	25.1	19.4	15.2
2023	13.6	13.2	19.2	24	27.2	30.8	32.5	31.3	28.3	25.4	19.4	15
2024	15	16.5	17.4	22.9	26.6	30.4	30.5	29.7	27.6	23.4	19.4	13.4

*Note: The empty cells indicate measurements missing from the original dataset.

Table 9. Identification and estimation of the missing values in the actual average monthly water temperatures' dataset [°C]

Years	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2018	15.7	16.3	20	22.6	26.9	32.9	31.6	30.8	31.2	26.5	19.8	16.1
2019	13.8	14.9	16.4	21.2	25.9	30.5	29.9	29.6	27.7	25	25	20.9
2020	13.3	14.6	18.5	22.1	25	28.3	32	30	30.3	26	19.8	14.5
2021	12.5	14.9	17.5	21.7	26.7	28.4	31.2	31.5	25.3	21.1	18.8	15.2
2022	11.8	13.4	15.5	22.1	25.9	29.9	32.1	31.1	30.2	25.1	19.4	15.2
2023	13.6	13.2	19.2	24	27.2	30.8	32.5	31.3	28.3	25.4	19.4	15
2024	15	16.5	17.4	22.9	26.6	30.4	30.5	29.7	27.6	23.4	19.4	13.4

RESULTS

The monthly average actual water temperature data and the monthly average water temperature data derived from Landsat satellite imagery during the study period were analyzed. The following statistical results were observed:

Regression analysis between the actual monthly water temperatures measured in the field at the Al-Hindiyah Barrage site and the average monthly surface water temperatures extracted from Landsat satellite imagery revealed a strong statistical correlation between the two data sets. From a statistical perspective, the linear regression analysis between actual and Landsat-derived average water temperatures revealed a strong relationship represented by the equation $Y = 1.3246X – 2.1929$ with a high coefficient of determination ($R^2 = 0.93$). This indicates that 93% of the variability in actual temperatures can be explained by satellite data, confirming the reliability of thermal remote sensing as an alternative or complementary tool to field measurements (Wang and Gastellu-Etchegorry, 2020).

The regression achieved a coefficient of determination (R^2) of 0.93, indicating that 93% of the variance in the actual monthly water temperatures can be explained by the Landsat satellite data. Figure 2 illustrates this strong correlation through the high degree of convergence between the observed and the estimated values from the satellite data.

To further validate the predictive efficiency of the linear regression, the Nash–Sutcliffe efficiency coefficient (NSE) was used as an additional indicator to assess the degree of agreement between the observed and the estimated values. The NSE was 0.89, which indicated high predictive ability and a great agreement in the field-measured surface water temperatures and in the satellite-extracted temperatures as observed in Figure 3. Based on the traditional criteria of hydrological and environmental research, NSE values above 0.75 are considered to have very high predictive power. Thus, the fact that the values of the R^2 and NSE are high confirms the strength and validity of the proposed regression and indicates the possibility of using the Landsat satellite remote sensing data as a valid source or supplement of field measurements in both multi-year water resources tracking projects and in regions where there is little field data.

For the actual water temperature, the minimum monthly average temperature was 11.8°C, recorded in January 2022, while the maximum monthly average temperature was 32.9°C in June 2018. For the Landsat data, the minimum monthly average temperature was 12.0°C, observed in January 2019, and the maximum monthly average temperature reached 40.8°C in August 2023. Extreme satellite-derived temperature values were visually inspected and quality-checked using the Landsat Level-2 quality assessment (QA) flags and surrounding pixel consistency to exclude cloud contamination or processing artifacts. To illustrate the variations across different years, the data were divided into three time periods presented in Tables 10, 11, and 12. Table 10 displays the monthly average temperature data for the period 2018–2019, Table 11 covers the period from 2020 to 2023, and Table 12 includes the data for 2024.

After comparing the actual water temperature data obtained from the Al-Hindiyah Barrage with

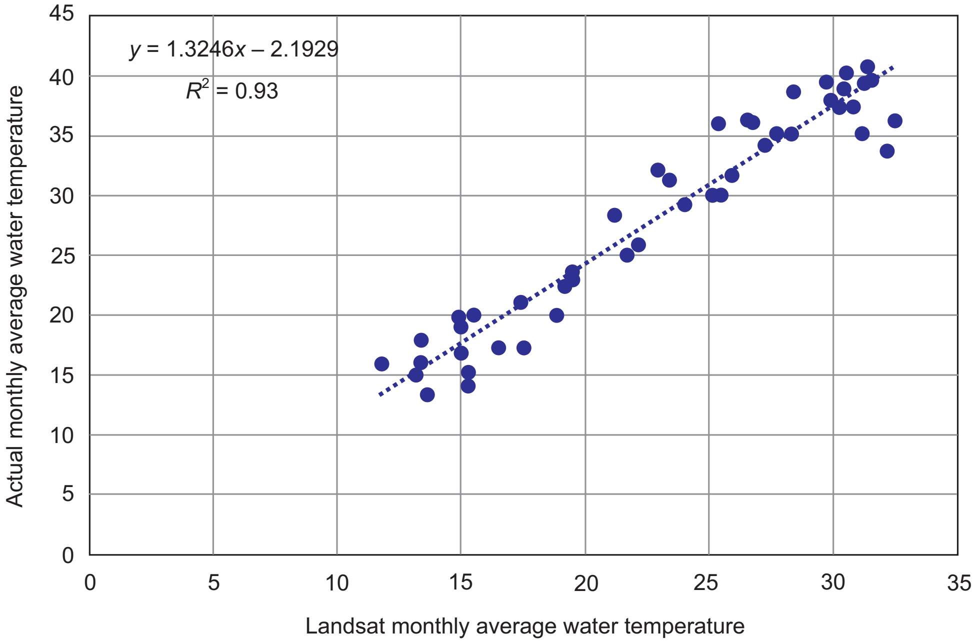


Fig. 2. Scatter plot showing the relationship between the actual average monthly water temperatures (y-axis) and Landsat-derived average monthly water temperatures (x-axis) during the study period (Source: Authors' own elaboration)

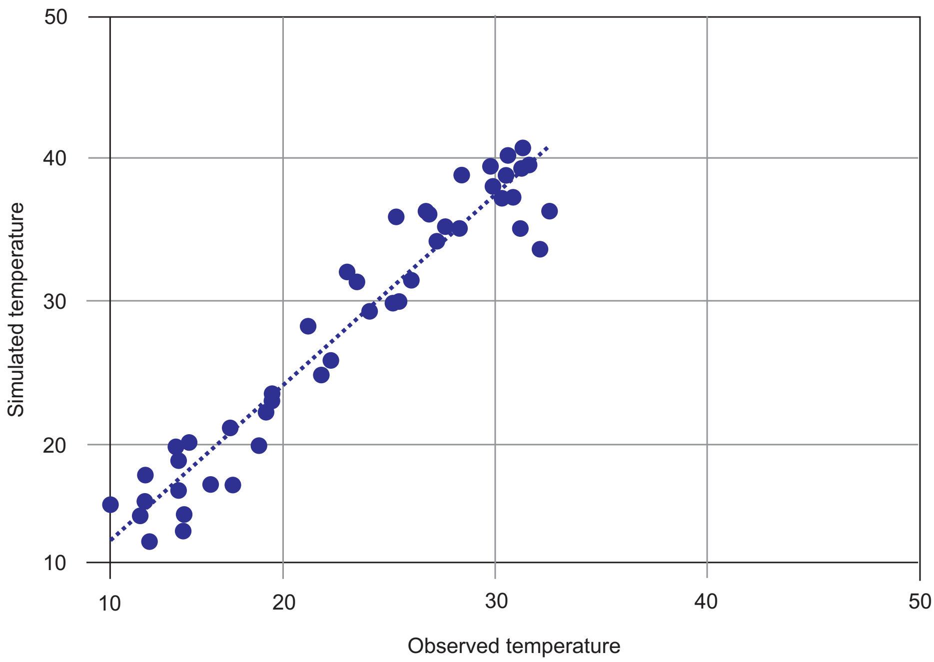


Fig. 3. Comparison of field-observed water temperatures with simulated water temperatures using Landsat satellite data at the location of the Al-Hindiyah Barrage (NSE = 0.89) (Source: Authors' own elaboration)

the satellite-derived data from Landsat, the analysis revealed that the lowest monthly average water temperature (12°C) was obtained from Landsat in January 2019, while the highest monthly average water temperature (40.8°C) was obtained from Landsat in August 2023. These results highlight the capability of Landsat data to accurately capture extreme variations in surface water temperature throughout the study period.

When comparing the results of this study with previous studies, such as McBean et al. (2022) ECO Lab study that recorded NSE values between 0.955 and 0.958 for simulating stream temperatures, the performance of the linear regression function analysis in this study is clearly high. The slight difference in values is attributed to the current study's reliance on satellite data and linear regression rather than complex hydrodynamic physical models.

This strong correlation demonstrates that Landsat satellite data provide a reliable representation of surface water temperatures in the study area, supporting their use as a supplementary or alternative source to in situ measurements, especially in periods or locations where field data are not available.

Table 10. Comparison of the actual and Landsatderived monthly average water temperatures [°C] for 2018 to 2019

Date	Actual monthly average	Landsat monthly average
Jan-2018	15.7	14
Feb-2018	16.3	14.6
Mar-2018	20	23.2
Apr-2018	22.6	30.3
May-2018	26.9	32
Jun-2018	32.9	33.4
Jul-2018	31.6	40
Aug-2018	30.8	37
Sep-2018	31.2	38.3
Oct-2018	26.5	19.9
Nov-2018	19.8	19
Dec-2018	16.1	15.3
Jan-2019	13.8	12
Feb-2019	14.9	18
Mar-2019	16.4	21
Apr-2019	21.2	26.2
May-2019	25.9	36.7
Jun-2019	30.5	38.7
Jul-2019	29.9	36.7
Aug-2019	29.6	37.1
Sep-2019	27.7	35.2
Oct-2019	25	31.3
Nov-2019	25	22.3
Dec-2019	20.9	13.5

Table 11. Comparison of the actual and Landsat derived monthly average water temperatures [°C] for 2020 to 2023

Date	Actual monthly average	Landsat monthly average
Jan-2020	13.3	15.1
Feb-2020	14.6	14.8
Mar-2020	18.5	20.6
Apr-2020	22.1	17
May-2020	25	31.9
Jun-2020	28.3	37.9
Jul-2020	32	39
Aug-2020	30	37
Sep-2020	30.3	35.9
Oct-2020	26	29.4
Nov-2020	19.8	21
Dec-2020	14.5	15.5
Jan-2021	12.5	13.3
Feb-2021	14.9	19.8
Mar-2021	17.5	17.3
Apr-2021	21.7	25
May-2021	26.7	36.1
Jun-2021	28.4	38.8
Jul-2021	31.2	39.4
Aug-2021	31.5	39.6
Sep-2021	25.3	36
Oct-2021	21.1	28.4

Date	Actual monthly average	Landsat monthly average
Nov-2021	18.8	20
Dec-2021	15.2	15.2
Jan-2022	11.8	15.9
Feb-2022	13.4	18
Mar-2022	15.5	20.1
Apr-2022	22.1	26
May-2022	25.9	31.6
Jun-2022	29.9	38
Jul-2022	32.1	33.8
Aug-2022	31.1	35.2
Sep-2022	30.2	37.4
Oct-2022	25.1	30
Nov-2022	19.4	23.6
Dec-2022	15.2	14
Jan-2023	13.6	13.3
Feb-2023	13.2	15
Mar-2023	19.2	22.4
Apr-2023	24	29.3
May-2023	27.2	34.3
Jun-2023	30.8	37.4
Jul-2023	32.5	36.3
Aug-2023	31.3	40.8
Sep-2023	28.3	35.2
Oct-2023	25.4	30.1
Nov-2023	19.4	23
Dec-2023	15	19

Table 12. Comparison of the actual and Landsatderived monthly average water temperatures [°C] for 2024

Date	Actual monthly average	Landsat monthly average
Jan-2024	15	16.9
Feb-2024	16.5	17.2
Mar-2024	17.4	21.1
Apr-2024	22.9	32
May-2024	26.6	36.4
Jun-2024	30.4	38.9
Jul-2024	30.5	40.2
Aug-2024	29.7	39.5
Sep-2024	27.6	35.3
Oct-2024	23.4	31.4
Nov-2024	19.4	23
Dec-2024	13.4	16

*Note: Blue in all the tables is used to show the minimum monthly water temperatures and their monthly averages, orange is used to show the maximum monthly water temperatures and their monthly averages, and yellow is used to show the missing values.

DISCUSSION

The results of the study indicate clear variations in the water temperature of the Euphrates River at the Al-Hindiyah Barrage between the years 2018 and 2024, with the lowest recorded actual monthly average temperature of 11.8°C in January 2022 and the maximum actual monthly average temperature of 32.9°C in the month of June 2018. The Landsat satellite data showed a wider range of temperatures, with a minimum of 12.0°C in January 2019 and a significantly higher maximum of 40.8°C in August 2023.

In comparison to in situ measurements, this observation accentuates the potential of remote sensing to detect extreme thermal occurrences or spatially restricted hotspots of temperature that could sometimes be difficult to note at ground-based monitoring stations due to low spatial density or temporal resolution (Ahmed et al., 2024). The fact that the temperatures were high in this work, particularly over 40°C, also points to the additional thermal stress on the aquatic ecosystem, and this observation is also in line with global and local warnings regarding the increase in surface water temperature (Hussein et al., 2023; Czernecki and Ptak, 2018). The waters with high temperatures directly endanger the health of aquatic organisms and consequently the sustainability of ecosystems because they reduce the dissolved oxygen level, augment the toxicity of pollutants, and alter numerous physical and biochemical processes in rivers that are fundamental to in industrial and agricultural operations (Hussein et al., 2023; McBean et al., 2022).

However, the regression shows that there is a mild inclination of the satellite data to exaggerate temperatures at stronger ranges, and this is anticipated since there are atmospheric effects and nighttime dissimilarity between surface emissivity and in situ measurements of water column temperatures. Thus, continuous calibration using ground data is necessary to enhance predictive accuracy and enable practical application.

Although Landsat satellites have exceeded their planned operational lifespan, which could potentially introduce instrumental drift in thermal infrared measurements, the use of Collection 2 Level 2 Analysis Ready Data (ARD) effectively mitigates such effects. The high agreement between satellite-derived and in situ measurements ($R^2 = 0.93$; NSE = 0.89) suggests that any influence of instrumental drift on the results is minimal, confirming the reliability of Landsat data for monitoring surface water temperature variations.

Reliance on satellite data facilitates continuous and comprehensive monitoring over large water bodies, overcoming logistical and geographical constraints faced by field measurements, especially in regions such as Iraq where monitoring stations are scarce (Al-Sultani and Al-Hadidi, 2023). This can be mitigated by combining remote sensing methods with statistical models like linear regression.

Importantly, temperature variation influences water quality as well as the spatial distribution and performance of aquatic organisms, suggesting that ongoing research is needed to assess the potential impacts of temperature on biodiversity and aquatic ecosystems (Deas and Lowney, 2000; Johnson et al., 2024). With further growth in atmospheric greenhouse gas emissions, the projections of global temperature rise will indeed become increasingly grim, and accurate satellite-based predictive models separating the environmental, social, and economic aspects of smart water management will be urgently needed (Imteaz et al., 2017).

Comparing the linear regression performance at Al-Hindiyah Barrage with previous studies, such as McBean et al. (2022) ECO Lab study, which recorded NSE values between 0.955 and 0.958, it becomes clear that the method used in this study provides accurate estimates of water temperatures despite using satellite data and statistical regression instead of complex physical models. The achieved value (NSE = 0.89) indicates the reliability of this method for monitoring thermal changes in the dam and assessing their impact on aquatic organisms, especially heat-sensitive species.

The outcome of the Al-Hindiyah Barrage study proves that the accuracy of measurements is high, which means that it is possible to note when the temperature of the water can be over the optimal temperature range of cold-water fish, since even minor temperature fluctuations in the summer have a negative impact on this group of organisms. Consequently, the findings of the study have made water management activities and the preservation of biodiversity in the Barrage scientifically justified.

The combination of satellite and ground-level images constitutes a positive development in the observation and evaluation of water resources at the Al-Hindiyah Barrage. This research focuses on this particular location because of the availability of data. Further research may be extended to the multi-layer, regional, or international levels to compare the water resources in Iraq and its neighbouring countries, in order to enhance adequate planning and adaptation measures to address the contemporary challenges.

CONCLUSION

This research has emphasized the performance of using a combination of Landsat 8 and Landsat 9 on the basis of surface water temperature value with in situ water measurements to track the thermal variation of the Euphrates River at Al-Hindiyah Barrage in the period from 2018 to 2024. The strong correlation ($R^2 = 0.93$) between the actual water temperature and the temperature provided by satellites implies that satellite imagery might prove to be an effective, affordable, and scalable continuous water temperature monitoring system that is cost-effective and adaptable in remote locations where ground-based data is barely available.

Water temperatures were also significantly different from month to month, with in situ temperatures of 11.8°C to 32.9°C and satellite estimates of 12°C to 40.8°C, indicating the dynamism of thermal regimes in arid areas becoming more influenced by the existing impacts. These soaring temperatures in places where there is water stress, such as Iraq, pose unbearable predicaments to water quality, the ecosystem, and water resource management.

To determine the efficiency of the developed predictive, the Nash–Sutcliffe Efficiency Coefficient (NSE) was employed, and the value was found to be 0.89. Such a high value signifies a great work of the a powerful capability to real river water temperature changes. This strengthens the validity of the suggested linear regression model in its ability to predict real water temperatures using satellite data.

This research presents a practical instrument for forecasting real water temperatures based on satellite information, hence providing an effective channel for enhancing proper decision-making in connection with environmental monitoring, allocation of water resources, and operation of infrastructures, and consequently, making society more resilient to climate change and anthropogenic forces. Further developments of this methodology are suggested, involving enhanced ambient environmental conditions estimation using multi-source data fusion and machine learning techniques, as well as using measurements in the field for continuous validation to minimize errors and improve model generalizability. This study demonstrates high predictive accuracy for surface water temperature at Al-Hindiyah Barrage, with strong agreement between satellite-derived and in situ measurements ($R^2 = 0.93$, NSE = 0.89). The integration of remote sensing and field data provides a cost-effective and reliable approach to monitoring water temperature in remote areas. However, the study is limited to a single barrage and relies on monthly average data. Future research should consider multi-site assessments, incorporation of additional environmental parameters, and continuous validation using field measurements to enhance the generalizability and applicability.

In summary, this work provides new recommendations to the scientific and water management communities about the need of coupling remote sensing at a regional scale with ground-based monitoring networks in order to manage and protect critical water resources sustainably, while the threat intensifies.

SOFTWARE AND TOOLS USED

The analyses and data processing in this study were conducted using IBM SPSS Statistics (Version 26), developed and distributed by IBM Corp., Armonk, NY, USA, and ArcGIS Desktop (ArcMap) Version 10.8, developed by Esri Inc., Redlands, CA, USA. All software was used under licensed academic versions available at the authors' institution.

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MIESIĘCZNE WAHANIA TEMPERATURY WÓD POWIERZCHNIOWYCH NA ZAPORZE AL-HINDIJA W IRAKU MIERZONE TECHNIKĄ TELEDETEKCJI

ABSTRAKT

Cel badania

Problemem badawczym niniejszego studium jest modelowanie i śledzenie zmian temperatury wód powierzchniowych w rzece Eufrat na zaporze Al-Hindija w Iraku w oparciu o pomiary in situ oraz dane z satelity Landsat 8 i 9 (2018–2024).

Materiał i metody
W przedstawionych badaniach do określenia średnich miesięcznych temperatur wód powierzchniowych wykorzystano metody GIS oraz metody statystyczne do przetwarzania zarówno obserwacji terenowych, jak i termicznych obrazów w podczerwieni, pochodzących z satelity Landsat. Zbiór danych Landsat zawierał około 4,8% brakujących punktów danych, podczas gdy pomiary terenowe in situ zawierały około 1,2% brakujących wartości. Brakujące dane zrekonstruowano za pomocą oprogramowania IBM SPSS Statistics (wersja 26) poprzez kompensację średniej, zastępując brakujące wartości średnią arytmetyczną z tego samego miesiąca w latach, dla których dane z analogicznego miesiąca były dostępne. Tak skonstruowane podejście zapewniło stabilny i wiarygodny szereg czasowy, umożliwiając modelowanie zależności między temperaturami mierzonymi na miejscu a temperaturami mierzonymi satelitarnie za pomocą prostej regresji liniowej. Skuteczność regresji liniowej w zaporze Al-Hindija została oceniona za pomocą współczynnika Nasha–Sutcliffe'a.

Wyniki i wnioski
W oparciu o zebrane dane stwierdzono, że temperatury wody in situ wykazywały znaczne miesięczne wahania (tj. rzeczywiste temperatury wody wahały się od minimum 11,8°C do maksimum 32,9°C), zaś dane satelitarne rejestrowały jeszcze większy rozrzut temperatur, od minimum 12,0°C do maksimum 40,8°C. Wysoce istotna korelacja ($R^2 = 0,93$) między zestawami danych pokazuje, że dla wartości temperatury wody uzyskanych z satelity Landsat współczynnik NSE osiągnął 0,89, co wskazuje na doskonałą zgodność między wartościami obserwowanymi a szacowanymi. Wyniki badania potwierdzają przydatność satelity Landsat do monitorowania temperatury wody, wspierania zarządzania zasobami wodnymi i ochrony ekosystemów. Integracja teledetekcji z metodami tradycyjnymi zwiększa dokładność oceny w procesie podejmowania decyzji środowiskowych i działań adaptacyjnych. Predykcyjna regresja liniowa, której zaletą są niskie koszty wykorzystania, wspomaga monitorowanie na obszarach o ograniczonej dostępności danych i na obszarach suchych.

Słowa kluczowe: temperatura wód powierzchniowych, SPSS; Landsat 8 i 9; zapora Al-Hindija