Jordanian Journal of Engineering and Chemical Industries

Print ISSN: 2616 - 9584 Online ISSN: 2617 - 720X

Assessing Thermal Pollution from Power Plants Using Landsat Imagery and Google Earth Engine: A Case Study of the Red Sea.

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Abstract

The impact of thermal pollution from a Shuqaiq Power and Desalination Plant on the southwestern coast of the Red Sea of Saudi Arabia was examined in this study. Using the JavaScript code on the Google Earth Engine (GEE) platform, thermal band 10 of the Landsat 8 OLI-TIRS satellite imagery was employed to analyze the land surface temperature (LST) at water intake and discharge sites during the summer and winter of 2023. The study revealed consistent temperature differences between these locations, with the most significant variations observed during the summer. The discharge temperatures in May reached approximately 43 °C, which is approximately 5 °C higher than the intake temperatures. These seasonal fluctuations were attributed to ambient conditions and operational intensity. Elevated water temperatures at discharge points pose potential risks to marine ecosystems, as they can drastically decrease oxygen solubility and create stressful conditions for aquatic life. These findings highlight the necessity for ongoing environmental monitoring and improved cooling technologies to minimize thermal pollution and protect local biodiversity. Remote sensing techniques have emerged as efficient methods for ensuring environmental compliance by identifying thermal plumes around facilities that release heated effluents into water bodies, such as power plants and similar industries.

Paper type: Research paper

Keywords: Thermal pollution, Water temperature, Power plants, Google Earth Engine (GEE), Remote sensing, Landsat 08 OLI-TIRS,

Citation: Abdullah, K., and M, Arshad " Assessing Thermal Pollution from Power Plants Using Landsat Imagery and Google Earth Engine: A Case Study of the Red Sea.", Jordanian Journal of Engineering and Chemical Industries, Vol. 8, No.1, pp: 1 - 8 (2025).

Introduction

Power plants are typically situated in proximity to coastal areas to meet cooling water requirements. Thermal pollution resulting from the discharge of heated water from power plants poses a significant environmental threat to aquatic ecosystems [1]. Waste heat is released into adjacent water bodies, where it is subsequently dissipated into the surrounding aquatic environment and atmosphere through convection and radiation mechanisms of heat transfer [2]. Temperature exerts a significant influence on gas solubility, which consequently impacts the concentration of dissolved oxygen (DO), an essential element for aquatic organism survival [1, 3]. Additionally, temperature modulates chemical processes, microbial activity, and water density, thus affecting nutrient cycles, organic matter decomposition, and hydrodynamic patterns [4, 5]. Traditional methods for monitoring thermal pollution typically involve direct water temperature measurements at a site [6]. However, these approaches often require substantial manual effort, are time-consuming, and may yield inaccurate results owing to advection and tidal influences. Consequently, there is an increasing demand for efficient and accurate methodologies for monitoring thermal pollution [7, 8, 9]. Remote sensing technology has emerged as a powerful tool for environmental monitoring, enabling the analysis of extensive geographical regions with precise temporal and spatial resolutions. Satellite-based sensors,

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Received 7 November 2024 Revised: 24 Dec 2024

Jordanian Journal of Engineering and Chemical Industries (JJECI), Vol.8, No.1, 2025, pp: 1- 8. Accepted 21 Feb 2025

such as those found on Landsat 08 and Landsat 9, equipped with thermal infrared sensors (TIR), are effective for identifying thermal plumes in both coastal and inland water bodies [10]. Using the Google Earth Engine (GEE) platform, these satellite images can be processed and analyzed to efficiently and accurately monitor thermal pollution [11, 12]. Remote sensing facilitates simultaneous monitoring of multiple power plants across extensive geographical regions, which constitutes an additional advantage. This capability is particularly valuable for comparative analysis, as it enables the evaluation of different facilities by assessing their impacts on the surrounding ecosystems. These comparisons can potentially drive progress throughout the industry, as policymakers endeavor to reduce thermal emissions and enhance efficiency [13]. Moreover, the utilization of platforms such as Google Earth Engine (GEE) facilitates the processing and analysis of extensive datasets, enabling real-time monitoring and investigation of thermal pollution trends over time [14]. This capability is crucial for regulatory authorities and policymakers, who require expertise to assess compliance with environmental regulations and ensure that power plants operate efficiently while minimizing their ecological impact [15]. Access to this platform requires the creation of an account, provided without charge for educational and research purposes.

Land surface temperature (LST) is a critical variable in the field of environmental science because it represents the thermal energy emitted by the Earth's surface. A comprehensive understanding of LST dynamics is essential for accurately assessing environmental changes, implications of landuse alterations, and presence of thermal pollution [16]. The precise determination of LST using remote sensing techniques depend on multiple critical parameters. These parameters include the employment of thermal bands for detecting surface temperature fluctuations, application of atmospheric correction methodologies to mitigate effects such as water vapor, and quantification of surface emissivity, which characterizes the efficiency of thermal energy emission. These elements play a fundamental role in ensuring accurate LST calculations and facilitating comprehensive environmental monitoring [17].

This study primarily investigated the use of remote sensing techniques to monitor and assess thermal pollution along the coast of the Red Sea for ecosystem protection. The principal focus is on power facilities that discharge heated effluents into surrounding waters. This research aims to employ JavaScript code to analyze Landsat 08 OLI-TIR images in GEE to accurately determine and quantify the extent of thermal pollution during both the summer and winter seasons. These findings demonstrate the efficacy of remote sensing as an expeditious and reliable method to ensure environmental compliance and monitor thermal pollution.

1 Materials and Methods

1.1 Description of Shuqaiq Power Plant

The Shuqaiq Power and Desalination Plant is situated on the southwestern coast of Saudi Arabia, in proximity to the extant Shuqaiq 01 facility. This installation, located 105 km south of Abha and 140 km north of Jizan, faces the Red Sea and serves as a vital source of potable water and electricity in the region.

The Shuqaiq Integrated Water and Power Plant (IWPP) was engineered to generate 850 MW of electrical power and desalinate 212,000 cubic meters of water per day. The facility's primary infrastructure consists of three Arabian heavy crude-oil-powered boilers that operate three condensing steam turbines for power generation. In addition, the plant incorporates a dedicated reverse osmosis unit for water desalination, ensuring a consistent supply of both electricity and potable water to adjacent regions.

1.2 Data obtained from satellite

The Landsat program, launched in 1972, is the longest-running initiative for obtaining satellite pictures of Earth. They have been crucial in environmental monitoring, land utilization, and climate change studies. The Landsat satellite series, jointly controlled by NASA and the USGS, was equipped with temperature sensors. The operational Landsat 8 and 9 satellites are outfitted with thermal infrared sensors (TIRS). Landsat 8 was chosen over Landsat 9 due to its extended operational duration, offering a more comprehensive dataset for historical research. The TIRS sensor consists of two thermal bands: Band 10, operating within the wavelength range of 10.60 to 11.19 micrometers, and Band 11, functioning within the wavelength range of 11.50 to 12.51 micrometers. TIRS bands were first obtained at a spatial resolution of 100 µm. Subsequently, they were resampled to a finer resolution of 30 m utilizing publically available data products. Prior research has shown that calibration discrepancies in band 11 might result in erroneous temperature measurements, especially in areas with elevated surface reflection. The USGS recommends that users avoid employing band 11 data from TIRS in quantitative analysis due to its elevated calibration uncertainty. This research sought to examine thermal anomalies in metropolitan regions with Landsat 8 TIRS data. Band 10 was chosen because to its superior thermal wave transmission and minimal upwelling induced by air radiation [12]. Consequently, in alignment with the current project objectives, band 10 of the TIRS meets the necessary criteria regarding radiometry, wavelength range, and spatial resolution. We employed monthly Landsat 8 data till 2023. The acquired data pertained to pathways 167 and 48, which covered the geographical area of interest throughout the study period. The satellite data utilized are enumerated in Table 1**.**

Table. 1 List of satellite data utilized in the current investigation**.**

Serial Number	Satellite	Sensor	Acquisition Date
1			Jan 20, 2023
2			Feb 21, 2023
3			Mar 25, 2023
4			Apr 10, 2023
5			May 19, 2023
6	LANDSAT-8	TIRS Band 10	Jun 29, 2023
7			Jul 22, 2023
8			Aug 23, 2023
9			Sep 17, 2023
10			Oct 3, 2023
11			N\A
12			Dec 22, 2023

1.3 Study Area and Data Collection

This research focused on the area surrounding the Shuqaiq Power Plant (SPP), located on Saudi Arabia's southwestern coastline near the Red Sea (longitude: 42.0811, latitude: 17.6421). Satellite imagery was obtained from the Landsat 8 OLI-TIRS Collection 2, Level 2 dataset, accessed through the Google Earth Engine (GEE). To capture thermal characteristics, data collection was limited to the period between April 1, 2023, and July 31, 2023. To ensure high-quality data for analysis, only images with less than 5% cloud cover were selected.

Fig. 1. Water Intake and discharge points. Image ©2024 Google Earth, Imagery ©2024 Airbus

1.4 Data preprocessing

The conversion of digital numbers (DN) to the Top of Atmospheric (TOA) Spectral Radiance for thermal infrared bands was accomplished using radiance rescaling factors [18]. This conversion process is crucial for extracting land surface temperature (LST) from satellite images. By applying these rescaling factors to the thermal band DN, the information is transformed into the TOA spectral radiance, which facilitates standardization for subsequent analysis. Specifically, a multiplication factor of 0.0000275 was applied to the optical bands (B1-B7), followed by a subtraction of 0.2 for correction. The thermal band (ST_B10) underwent scaling with a factor of 0.00341802, and subsequently, an offset of 149.0 was added to transform it into brightness temperature measured in Kelvin.

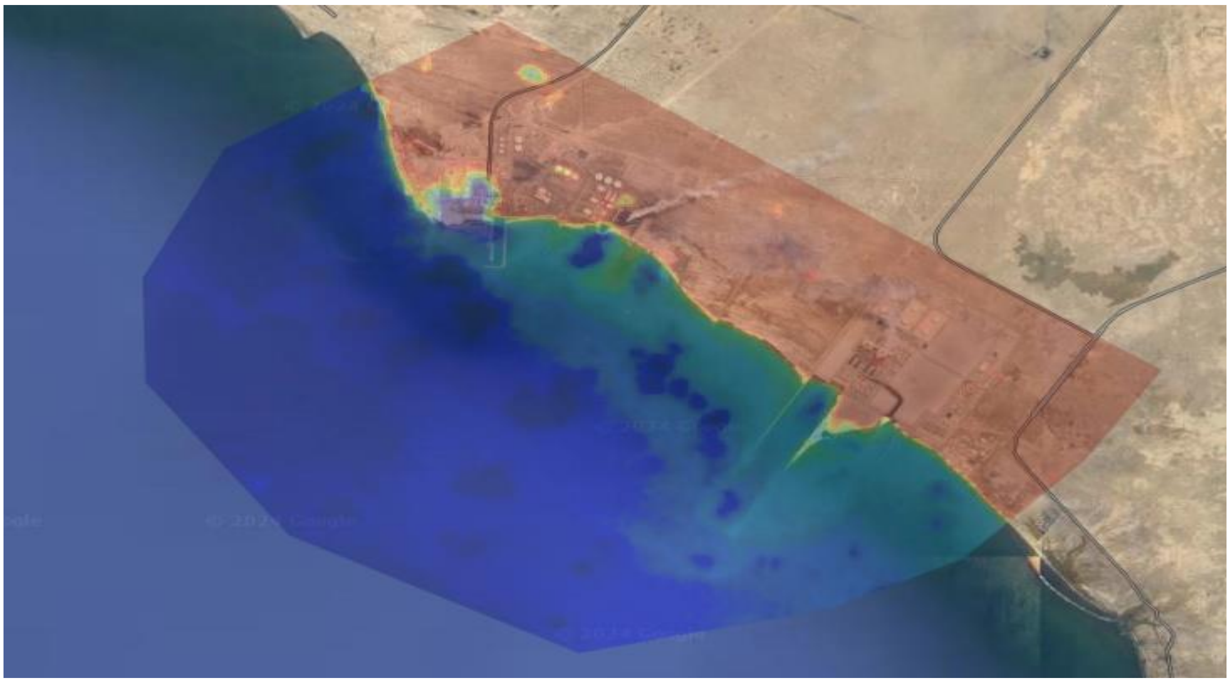

Fig. 2. Thermal Imagery of the Shuqaiq Power Plant Study Area from Google Earth Engine.

1.5 Retrieval of Land Surface Temperature (LST)

Thermal band 10 (ST_B10) of Landsat 8 was utilized to directly obtain the Land Surface Temperature (LST). The brightness temperature data was converted to Celsius by subtracting 273.15. A unique color scheme was implemented on the LST layer to more clearly emphasize the temperature fluctuations within the study area.

1.6 Data visualization and analysis

The Land Surface Temperature (LST) layer was visualized using specific parameters, with temperatures spanning from 18.47 °C to 52.50 °C, and a specially selected color scheme to highlight temperature differences. To determine the lowest and highest LST values within the research area, the (reduceRegion) function was employed. This function applies a reducer across the entire region to identify extreme values.

1.7 Data Export

Finally, the LST information was moved to Google Drive as GeoTIFF files, preserving a 30 m resolution to ensure detailed, high-quality results. The images were then optimized for cloud-based storage and analysis to improve the efficiency.

2 Results and Discussion

1.2 Analysis of Land Surface Temperature (LST)

In 2023, satellite imagery from the Landsat 8 OLI-TIRS platform was utilized to conduct monthly assessments of Land Surface Temperature (LST) at the Shuqaiq Power Plant's intake and outflow sites. This data analysis aimed to assess the impact of power plant's operations on the adjacent marine environment, with a particular emphasis on thermal pollution. The monthly LST readings at the input and discharge points, along with their corresponding temperature differences, are listed in **Table 2**. The temperature disparity between these locations serves as a critical indicator of thermal pollution, because it represents the excess heat released into the surrounding area.

Table 2. Monthly temperature data at water intake and discharge points obtained from Landsat 8 satellite images in 2023.

Acquisition Date	Temperature at the intake point(°C)	Temperature at the Discharge point (°C)	Temperature Difference (°C)
Jan 20, 2023	30.7717	33.3181	2.5464
Feb 21, 2023	27.9313	31.1203	3.1890
Mar 25, 2023	21.8814	23.5221	1.6407
Apr 10, 2023	35.6048	38.4793	2.8745
May 19, 2023	37.9495	43.0082	5.0587
Jun 29, 2023	43.0458	47.6123	4.5665
Jul 22, 2023	36.7327	40.6498	3.9171
Aug 23, 2023	40.6190	44.8471	4.2281
Sep 17, 2023	36.8216	39.2655	2.4439
Oct 3, 2023	39.2108	41.6923	2.4815
Dec 22, 2023	33.3831	35.6937	2.3106

Figure 3 illustrates the monthly Land Surface Temperature (LST) at both the intake and discharge sites, showing seasonal fluctuations. The findings indicate a persistent pattern where the discharge temperatures surpass the intake temperatures, with the most significant temperature disparities observed during the summer period (April to August). In particular, the LST at the discharge location in May exhibited an increase of approximately 5°C compared to the intake site, reaching approximately 43°C, while the intake site registered approximately 38°C. This trend suggests that the thermal output of the plant is most pronounced during times of high operational

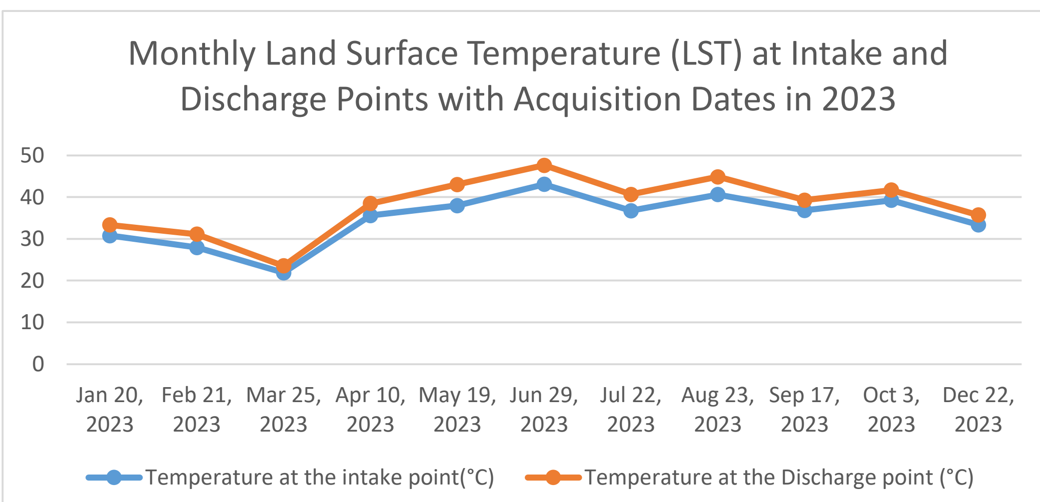

Fig. 3. Monthly Land Surface Temperature (LST) at Water Intake and Discharge Points with Acquisition Dates in 2023.

2.2 Seasonal Variations and Thermal Pollution

Temperature variations in the Red Sea are influenced by seasonal patterns and anthropogenic factors [19]. Significant fluctuations were observed in the temperature differences between the intake and outflow points from the Shuqaiq power plant during the summer. [19] also confirmed that thermal discharge from a power plant, combined with eutrophication, led to shifts in phytoplankton communities in Xiangshan Bay, East China Sea, suggesting that power plant operations, if not properly monitored, can impact local water temperatures and ecosystems. The more pronounced temperature gap in summer can be attributed to the higher ambient temperatures and increased power generation demands, likely resulting in a greater thermal load on the cooling system.

Conversely, the temperature variations were less pronounced in January and December, with the intake and discharge LST values being more closely aligned at approximately 30°C and 35°C, respectively. This seasonal trend suggests that both the surrounding climate conditions and level of operational activity significantly influence the thermal impact of the plant

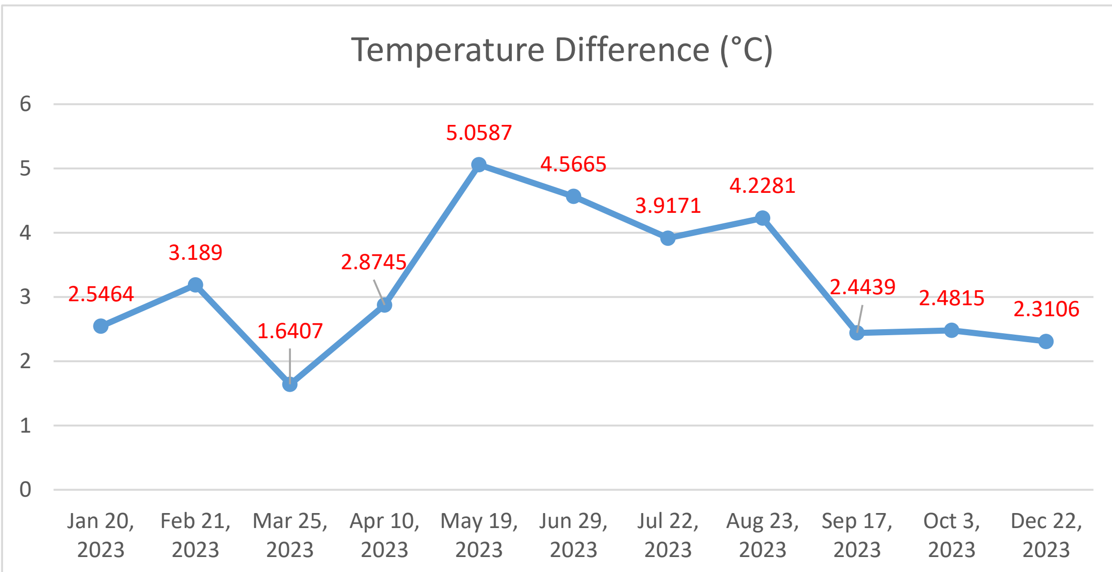

Fig. 4. Temperature differences between the Water intake and discharge points.

Conclusions

This study effectively employed JavaScript code on the Google Earth Engine platform to analyze Landsat 08 OLI-TIR images, illustrating the efficacy of remote sensing technology in monitoring thermal pollution from power plants. Future study may investigate the use of supplementary satellite data and sophisticated machine-learning algorithms to improve the precision and efficacy of thermal pollution monitoring.
Prospective Outlook Future study may investigate the use of supplementary satellite data and sophisticated machine-learning algorithms to improve the precision and efficacy of thermal pollution monitoring.

Acknowledgments

This research was made possible through the generous financial and academic support of King Khalid University, for which I am deeply grateful. I extend my heartfelt thanks to Dr. Muhammad Arshad for his exceptional guidance and mentorship throughout this study. The successful completion of this study was greatly facilitated by the resources and assistance provided by the Department of Chemical Engineering.

Nomenclature

DO	=Dissolved Oxygen	[mg/L]
DN	=Digital Number	[raw satellite data]
GEE	=Google Earth Engine	[-]
IWPP	=Integrated Water and Power Plant	[-]
LST	=Land Surface Temperature	[°C]
OLI	=Operational Land Imager	[-]
Path/Row	=Satellite Tile Coordinates	[-]
ST_B10	=Surface Temperature from Band 10 (Landsat 8)	[-]
TIRS	=Thermal Infrared Sensor	[-]
TOA	=Top of Atmospheric Radiance	[-]

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