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Long-Term Monitoring of Coastal Water Quality Using Sentinel-2 Satellite Images and Google Earth Engine: The Case Study Izmir and Erdek Bays

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Abstract

Coastal waters, crucial for ecology, are threatened by pollution and eutrophication caused by human activities. Monitoring water quality, particularly parameters such as Chlorophyll-a (Chl-a) and Total Suspended Matter (TSM), is essential for sustaining biodiversity and managing aquatic ecosystems. Although in-situ measurement methods are considered reliable, they are expensive, labour-intensive, and spatially limited, which poses challenges for large-scale monitoring. Satellite remote sensing offers an alternative, providing large-scale data for assessing water quality over time. This study utilizes Sentinel-2 Level-1C (Top of Atmosphere reflectance) satellite imagery and the Google Earth Engine (GEE) platform to monitor temporal changes in Izmir and Erdek bays from 2018 to 2024. Indices such as the Normalized Difference Chlorophyll Index (NDCI) and the Normalized Difference Aquatic Vegetation Index (NDAVI) were used for a time series analysis to evaluate water quality, showing high values in both study areas during 2020, particularly in summer, when the correlation was strongest. The Coast 2 Regional CoastColor (C2RCC) algorithm was applied to retrieve Chl-a and TSM values. According to the time series analysis results, Chl-a and TSM parameters were calculated as 7.87 mg/m^3 and 2.51 g/m^3 and 10.18 mg/m^3 and 1.15 g/m^3 respectively for Izmir and Erdek bays. Results also show a correlation between the indices and water quality parameters. This suggests that satellite-based methods effectively monitor complex aquatic ecosystems without in-situ measurements. In order to increase accuracy and reliability, future work involves integrating advanced modelling techniques, such as deep learning networks, with remote sensing data into the GEE cloud-based platform.

1. Introduction

Coastal waters are of great importance both ecologically and economically. However, they have become increasingly vulnerable due to rising population pressure and industrialization in coastal areas (Thorne-Miller, 1999). As a result, eutrophication due to natural and anthropogenic impacts threatens these areas. Eutrophication can significantly affect the marine ecosystem and humans (Anderson et al. 2002). Failure to develop strategies for effective management of resources results in increased risks to human health, property, economic viability, and damage to the benefits derived from marine ecosystems (Pettorelli et al. 2014). Additionally, harmful algal blooms (HABs) significantly impact water quality (Joshi et al. 2024; Kramer and Abel, 2024; Zhang et al. 2024). Therefore, the government or relevant partners must continuously monitor these areas to ensure effective and sustainable coastal management. Traditional monitoring methods, which involve direct water quality measurements through in-situ data collection, provide accurate and reliable information but are limited in spatial and temporal coverage (Bierman et al. 2011). Moreover, applying in-situ collection methods across large areas is a labour-intensive process that requires high costs (Gehl and Rice, 2007). Remote sensing technologies provide significant cost and time efficiency for detecting and monitoring water quality parameters in coastal areas. These technologies provide significant savings in both time and cost, making them a valuable tool for large-scale monitoring efforts. Remotely sensed images are widely used in the monitoring and detection of water quality data (Karthick et al. 2024; Wang et al. 2024; Zhang et al. 2024; Zhong et al. 2024). For example, Bondur et al. (2021) analyzed the causes of the harmful algal bloom (HAB) along the Kamchatka coast in 2020 using a long-term time series based on satellite data. This study evaluated indicators such as sea surface height (HYCOM), temperature (NOAA OISST), chlorophyll-a (Chl-a) concentration (MODIS Ocean Color SMI), surface parameters (Sentinel-1), and suspended matter (TSM) characteristics (Sentinel-2). The findings revealed that before the harmful algal bloom (HAB), temperatures exceeded 6°C, and variability in water levels led to nutrient transport. During the HAB, Chl-a concentrations rose to 15 mg/m³, and a strong correlation was observed between HAB regions and areas with noticeable surface material. Increased river flow also elevated TSM concentrations above 10 mg/m³, contributing to the nutrient influx. Maslukah et al. (2023) investigated the prediction of water quality parameters using Sentinel-2 satellite imagery in coastal waters around the Marine Science Techno Park. The study used in-situ measurements to validate the methodology and reported RMSE, bias, and MAPE values of 21.17 mg/L, -10.76, and 31.52% for TSS, and 1.04 µg/L, 0.25, and 35.83% for Chl-a, respectively. Results indicated that Chl-a and TSM values retrieved using Sentinel-2 images were overestimated and underestimated, respectively.

Accurate determination of water quality parameters such as Chla and TSM with remote sensing technologies depends on reflectance measurements (Alcântara, 2018). Therefore, the reliability of reflectance measurements is critical for ensuring the validity of water quality data. Errors in reflectance measurements can lead to inaccurate parameter detection, which undermines the reliability of the results. Various distortions can occur during image acquisition due to geometric factors, requiring a process known as atmospheric correction (FallahAdl et al. 1996). The Case 2 Regional Coast-Color (C2RCC), an atmospheric correction algorithm, was developed using MERIS images for turbid coastal and inland water areas (Doerffer and Schiller,2007). Using the neural networks of the C2RCC algorithm, water quality information such as Chl-a and TSM can be estimated (Ogashawara et al. 2021; Soriano-González et al.

2022). Numerous studies have successfully applied the C2RCC processor to retrieve these parameters from Landsat-8, Sentinel-2, and Sentinel-3 images, particularly in coastal waters (Giannini et al. 2021; Masoud, 2022; Lock et al. 2023; Varghese et al. 2024).

The Google Earth Engine (GEE) platform, introduced in 2011, has become a widely used tool for processing and analyzing satellite images in remote sensing (Kumar ve Mutanga, 2018). Quang et al. (2022) conducted a study on the long-term Chl-a concentration change in Ha Long Bay using the cloud-based GEE platform. Chl-a values calculated from Sentinel-2 MSI images by ocean chlorophyll 2-band algorithm were compared with NOAA's global-scale calibrated weekly data. The results showed a strong correlation, with $R^2 = 0.83$ and RMSE = 2.55. The platform enables real-time calculation of spectral indices at the user's request (Amani et al. 2020). Spectral indices such as the Normalized Difference Aquatic Vegetation Index (NDAVI) and the Normalized Difference Chlorophyll Index (NDCI) are valuable tools for mapping aquatic vegetation and estimating Chl-a concentrations, respectively (Mishra and Mishra, 2012; Villa et al., 2013). Time-series analysis using these indices allows for monitoring temporal changes (Sidhu vd., 2018; Zhu vd., 2019; Cao vd., 2020). HAB detection and multi-temporal monitoring studies have been performed effectively using the GEE. For example, Colkesen et al. (2024a) evaluated Sentinel2 imagery from seven dates to detect HAB in Lake Burdur, using FAI and AFAI indices with time-series analysis on the GEE platform. Similarly, Das et al. (2024) examined water quality changes in Lake Chilika using NDCI, NDTI, and AWEI spectral indices.

The main objective of this study is to retrieve water quality parameters (Chl-a and TSM) by applying the C2RCC atmospheric correction algorithm to multi-temporal Sentinel-2 satellite imagery of Izmir Bay and Erdek Bay, located in different geographical regions of Türkiye, using cloud-based GEE platform. The relationships between these parameters and NDCI and NDAVI spectral indices were analyzed temporally and spatially by creating time-series data from Sentinel-2 images. Seasonal trends in these indices were also evaluated regarding water quality parameters.

2. Methodology

2.1 Study Area

Izmir Bay and Erdek Bay, two important bays of Türkiye, were selected as the study areas. Izmir Bay, one of the largest gulfs in the country, is located on the western coast of the Anatolian peninsula and connects to the eastern Aegean Sea coast (Figure 1a). It also hosts Türkiye's second-largest port (Aksu, 1998). The bay is about 20 km wide and 40 km long, and the floor is approximately 5-7 km wide and 24 km long (Sayın, 2003). Its surface area and volume are 500 km^2 and 11.5 billion m^3, respectively (Kucuksezgin, 2011). Chemical inputs from natural and anthropogenic sources, including industrial activities, discharged into the bay through the main sewage outlets, contribute to eutrophication and pollution (Balcı and Türkoğlu, 1993; Yelekci et al. 2021). Izmir Bay is divided into three distinct regions: the inner, middle, and outer gulf, due to its topographical and hydrological characteristics (Aksu, 1998; Mavili and Sever, 2002). As a result, the bay's environmental dynamics and pollution processes vary between these regions.

In Figure 1b, the coastline of Erdek Bay, a semi-enclosed basin located in the southwestern part of the Sea of Marmara on the northwestern coast of the Anatolian peninsula, is shown. Administratively, it falls within the borders of Balıkesir province. The bay's coastline is 130 km long and has a maximum depth of 55 m. Gönen Stream is the only freshwater inflow to the bay (Vardar, 2006; Keskin, 2007). Erdek Bay experiences pressure from point and diffuse pollution sources, including tourism-related activities (Tan, 2021). Seagrass (Posidonia oceanica) is observed along the shores of Paşalimanı Island, located in the northern part of the bay (Cirik et al., 2010; Gönülal et al., 2023).

In the study, 60 sample points (38° 23' 2.112"N, 26°50' 59.9748E; 38°27' 26.7084"N, 27°8' 36.528"E) corresponding to the inner and central parts of the Izmir Bay, an economically and strategically significant bay in the southwest of Türkiye, were analyzed. Similarly, values (indices and water quality parameters) obtained from 60 sample points (40° 18' 29.8296 "N, 27° 19' 14.5092" E; 40° 27' 10.5156 "N, 27° 51' 20.8872" E) for Erdek Bay were analyzed.

Figure 1. a) Izmir and b) Erdek bay study area location and distribution of sample points.

2.2 Dataset

Satellite imagery plays a critical role in providing up-to-date Earth data, performing temporal analysis and monitoring environmental changes around the world. Advances in satellite remote sensing technology have revolutionized approaches to monitoring the Earth's surface. The use of Sentinel-2 multispectral satellite images by European Space Agency (ESA) as a part of the Copernicus Program has significantly enhanced Earth Observations capabilities. Sentinel-2 satellite imagery offers higher spatial resolution (10 m) and temporal resolution of about 5 days, along with red edge bands, compared to other medium spatial resolution imagery (Phiri et al. 2020). In addition, Sentinel-2 sensor includes 13 spectral bands: four with a spatial resolution of 10 meters, six at 20 meters, and three at 60 meters (Richter et al. 2011).

3. Application

The study evaluated the potential use of multi-temporal spectral indices calculated on the GEE platform for the estimation of water quality parameters. To achieve this, six key steps were followed: (1) identification of satellite imagery and fitting, (2) processing of data on spectral bands and calculation of spectral indices, (3) generating multi-temporal time series of indices, (4) obtaining satellite imagery at the peaks of the time series, (5) estimating water quality parameters from satellite imagery while determining spectral indices, and (6) conducting correlation-based analysis of the results (Figure 2).

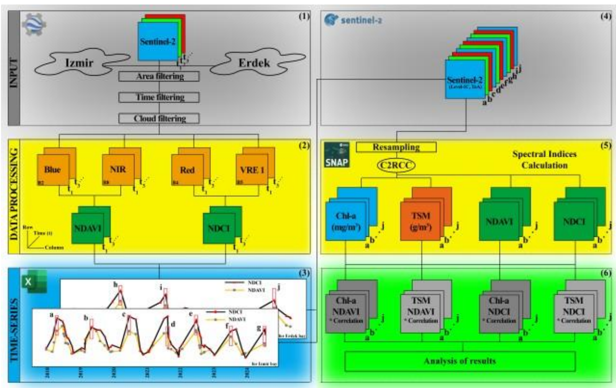

Figure 2. Overview of the study workflow.

3.1 Spectral Indices

In this study, the basic mathematical equations for the calculation of NDAVI and NDCI indices used for water quality monitoring are explained in detail (Table 1). It should be noted that in the table, B2, B4, B5 and B8 represent Band 2 (Blue), Band 4 (Red), Band 5 (Vegetation Red Edge-1) and Band 8 (NIR) of Sentinel-2 imagery, respectively. The NDAVI was designed to map vegetation cover in aquatic environments (Villa et al. 2013). Using remote sensing data, NDCI was developed to estimate Chl-a concentrations in turbid and productive waters, particularly in bays and coastal areas (Mishra and Mishra, 2012). The NDCI spectral index has been widely used to estimate water quality parameters in coastal areas (Natarajan et al. 2024). Numerous studies have utilized NDAVI and NDCI indices to monitor water quality. For example, Colkesen et al. (2024b) analyzed water quality parameters from samples collected in the Sakarya River during the phenological development of maize and correlated them with Sentinel-2 images. The study results showed significant changes in water quality parameters during the maize crop growth period. Spectral indices such as NDAVI, NDCI, and Automatic Musilage Extraction Index (AMEI) calculated using Sentinel-2 imagery were found to have strong correlations with water quality parameters.

Spectral Index	Formula
Normalized Difference Aquatic Vegetation Index (NDAVI)	(B8- B2)/ (B8+ B2)
Normalized Difference Chlorophyll Index (NDCI)	(B5- B4)/ (B5+ B2)

Table 1. Spectral index formulas used in the study.

3.2 Case 2 Regional Coast-Color (C2RCC) Atmospheric Correction Algorithm

Case-2 Regional processor, introduced by Doerffer and Schiller (2007), was developed as an atmospheric correction method based on artificial neural networks and named Case 2 Regional Coast-Color (C2RCC). The C2RCC processor processes top-ofatmosphere images (ToA) acquired by various sensors to minimize the effects of the atmosphere and buttom-ofatmosphere reflectance (BoA) images are generated from data. Furthermore, the output data includes BoA reflectance values as well as a range of water quality products based on inherent optical properties (IOP) such as Chl-a and TSM (Ogashawara et al. 2021; Soriano-González et al. 2022). The processor within the SNAP software published by ESA uses C2RCC, C2X and C2X-COMPLEX artificial neural networks to predict water quality parameters. Also, C2RCC has a higher prediction performance than the other networks (Cuartero et al. 2023). Relationships between IOPs and water parameters are sitespecific according to region and seasons (Brockmann et al, 2016). On the other hand, the processor uses parameters such as mean salinity (PSU), water surface temperature (°C), mean elevation (m) and atmospheric data to predict optimal Chl-a and TSM values (Virdis et al. 2022).

3.3 Cloud-based Google Earth Engine platform

Google developed the cloud-based GEE platform in 2011 to efficiently solve big data analysis challenges. The GEE stores petabytes of data and offers a wide set of functions that allow users to perform multi-temporal analysis (Amani vd., 2020). Furthermore, users utilize open-source and extensible scripts based on JavaScript or Python programming language to process remote sensing data in GEE (Johansen vd., 2024). The GEE platform provides free access to various data sets based on remote sensing optics (Landsat, Sentinel, MODIS and NOAA AVHRR), radar satellite images, ALOS digital altitude model, surface temperature and meteorology. One of the most important advantages of its platform is the great potential it offers in the rapid processing and analysis of high-dimensional data by combining big data and cloud computing (Xiaona vd., 2022). The platform has many applications, such as land use/land cover, flood and forest mapping (Chen vd., 2017; Saah vd., 2019; Uddin vd., 2019).

4. Result and Discussion

4.1 Time-series analysis

In order to determine the temporal distribution of Sentinel-2 images acquired during the peak dates of water quality parameters in the study areas, time series analyses based on NDAVI and NDCI indices specific to water quality parameters were performed on the cloud computing platform GEE. For this purpose, filtering process was applied to create an image collection in GEE. First, a polygon representing the boundaries was prepared to filter the study areas and imported into GEE code editor as an asset. A time filter was applied to monitor water quality parameters over a long-term period, covering the interval from January to September 2018 through 2024. The time filter was applied twice to ensure consistent intervals. Finally, a cloud filter was applied to images with less than 5% cloud cover. However, images over the study areas were manually investigated, especially for cloud-filtered images. Reason for the investigation is to identify images that are not clouds but are removed by cloud filtering. As a result of, the time series analysis resulted in a final image collection of 55 images for Izmir Bay and 24 images for Erdek Bay.

Based on the results of time-series analysis, the dates when the spectral indices reached their peaks were identified. Spectral indices (i.e. NDAVI and NDCI) specific to water quality parameters in the study areas were calculated for all images in the filtered final collection and the resulting time-series graphs are shown in Figure 3. According to the time-series graphs, the temporal changes in NDAVI and NDCI spectral index values showed similar trends. In Izmir Bay, the index values reached their highest levels on May 23, 2018; June 7, 2019; July 21, 2020; September 24, 2021; July 26, 2022; August 15, 2023; and August 19, 2024 (Figure 3a). On the other hand, peak values in Erdek Bay were observed on July 22, 2019; October 4, 2020; and August 30, 2023 (Figure 3b). The analysis showed that NDAVI and NDCI spectral indices increased notably during summer and dropped to lower values during winter. Similar to findings in the literature, these indices were found to be sensitive to seasonal variations and water quality was assessed to be higher in winter (Kamboj and Kamboj, 2019; Hammoumi et al. 2024). In addition, total of 10 Sentinel-2 images selected from the time-series analysis for both study areas were used as the primary dataset for the prediction of water quality parameters.

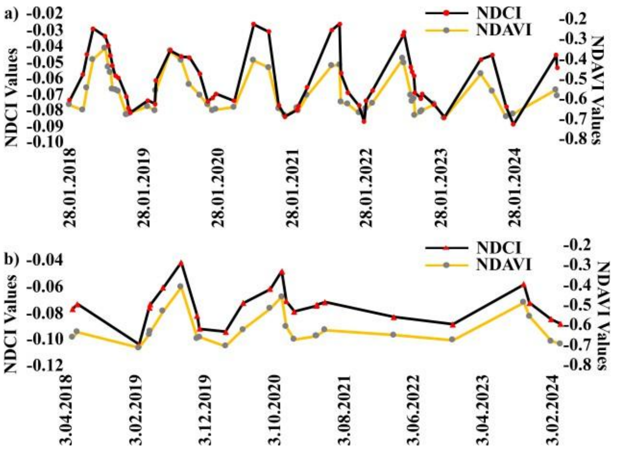

Figure 3. Time series graphs for a) Izmir bay b) Erdek bay.

4.2 Analysis of Spectral Indices

This study calculated NDAVI, a spectral index used to map vegetation cover in aquatic environments, and NDCI, which is frequently applied to estimate Chl-a content. The "Band Maths" tool under the Raster menu in the Sentinel Application Platform (SNAP) v9.0.0 version released by ESA was used to calculate spectral indices. Statistical information such as minimum, maximum and mean values of NDAVI and NDCI indices were obtained at different times using sample points in both study areas (Table 2). For Izmir bay, the highest NDAVI value was observed on June 7, 2019, while the highest NDCI value was recorded on July 21, 2020. On the other hand, the lowest values for both NDAVI and NDCI were obtained on September 24, 2021. In Erdek Bay, the highest and lowest values for NDAVI and NDCI were occurred on July 22, 2019 and August 30, 2023, respectively.

	No	NDAVI			NDCI		
		Min	Max	M	Min	Max	M
Izmir bay	a	-0.61	-0.28	-0.41	-0.09	0.07	-0.04
	b	-0.45	-0.32	-0.37	-0.09	0.01	-0.04
	c	-0.51	-0.35	-0.41	-0.08	0.09	-0.03
	d	-0.70	-0.21	-0.63	-0.15	0.18	-0.07
	e	-0.59	-0.30	-0.39	-0.08	0.14	-0.04
	f	-0.58	-0.39	-0.49	-0.13	0.03	-0.06
	g	-0.68	-0.44	-0.57	-0.13	0.05	-0.05
Erdek bay	h	-0.46	-0.35	-0.41	-0.09	-0.01	-0.04
	i	-0.53	-0.36	-0.48	-0.07	-0.03	-0.05
	j	-0.60	-0.42	-0.52	-0.08	-0.04	-0.06

Table 2. Statistical values for spectral indices.

4.3 Retrieval of water quality parameters using Sentinel-2

This study utilized the artificial neural network-based C2RCC atmospheric correction algorithm to retrieve water quality parameters, specifically Chl-a and TSM. To enable the C2RCC network to predict these indicators, parameters such as ozone (tcwv) and air pressure at sea level (msl) were produced at coresolution using the European Centre for Medium-Range Weather Forecasts (ECMWF) dataset on Sentinel-2 satellite images. In addition, input parameters such as salinity, temperature and elevation were obtained from Hybrid Coordinate Ocean Model (HYCOM), National Oceanic and Atmospheric Administration (NOAA) and Shuttle Radar Topography Mission (SRTM) datasets, corresponding to the study areas and dates. Using the C2RCC module under Thematic Water Processing in ESA SNAP v9.0.0, Chl-a and TSM parameters were extracted from Sentinel-2 satellite images for both study areas and observation dates (Table 3). Table 3 presents statistical data, including the minimum, maximum, and mean values for Chl-a and TSM derived from sample points within the study areas. For Izmir Bay, the highest Chl-a value was observed on July 21, 2020, while the highest TSM value was obtained on May 23, 2018. Conversely, the lowest values Chl-a and TSM values were observed on June 07, 2019 and September 24, 2021, respectively. In Erdek Bay, the highest and lowest Chl-a and TSM values were recorded on October 04, 2020 and August 30, 2023, respectively.

	No	Chl-a (mg/ m^3)			TSM (g/ m^3)		
		Min	Max	M	Min	Max	M
Izmir bay	a	0.97	21.37	10.43	1.58	9.31	5.88
	b	1.58	18.43	7.79	2.33	9.53	5.22
	c	1.36	20.97	11.48	1.25	9.51	4.39
	d	0.00	20.36	8.49	0.00	11.63	2.85
	e	0.10	19.89	7.87	0.08	13.95	3.21
	f	0.15	21.87	8.77	0.18	7.64	3.89
	g	0.17	20.72	7.87	0.51	7.04	2.51
Erdek bay	h	0.14	5.18	1.47	0.12	2.56	0.75
	i	0.19	25.88	10.18	0.09	3.25	1.16
	j	0.21	4.67	1.12	0.06	1.14	0.52

Table 3. Statistical values for water quality parameters retrieved using Sentinel-2.

4.4 Relationship between spectral indices and water quality parameters

The relationship between the NDAVI and NDCI indices calculated using Sentinel-2 satellite imagery and the retrieved Chl-a and TSM water quality parameters was assessed through correlation analysis (Table 4). For Izmir Bay, a strong correlation of 0.8125 value was observed between Chl-a parameter and the NDAVI index on August 19, 2024. In contrast, a correlation value 0.7158 indicated a relatively lower relationship between the TSM parameter and NDCI index. For the other study area, Erdek Bay, a robust correlation was found between the Chl-a parameter and the NDCI index on August 30, 2023, while the strongest correlation between TSM and the NDAVI index occurred on October 4, 2020. This disparity is attributed to the network's limited transfer capacity, especially coastal areas. Furthermore, the high correlation values recorded in Izmir Bay on August 19, 2024, can be linked to significantly increased pollution levels in recent years compared to earlier periods.

	No	Chl-a (mg/ m^3)		TSM (g/ m^3)	
		NDAVI	NDCI	NDAVI	NDCI
Izmir bay	a	0.62	0.65	0.01	-0.20
	b	0.55	0.47	-0.16	-0.21
	c	0.31	0.46	0.16	0.41
	d	-0.25	0.15	-0.04	0.35
	e	-0.43	0.06	-0.63	0.29
	f	0.67	0.50	0.26	0.14
	g	0.81	0.67	0.60	0.71
Erdek bay	h	0.11	-0.29	-0.12	-0.42
	i	-0.11	-0.16	-0.52	-0.57
	j	-0.24	-0.33	0.17	-0.00

Table 4. Correlation-based relationship values between spectral indices and water quality parameters.

5. Conclusions

This study examined whether NDAVI and NDCI spectral indices derived from Sentinel-2 imagery could serve as substitutes for Chl-a and TSM water quality parameters. The analysis focused on the correlation between spectral indices and these parameters. Results indicated a strong correlation between the spectral indices and water quality parameters on August 19, 2024, particularly in Izmir Bay, where pollution levels were notably high. In contrast, the correlations observed in Erdek were relatively weaker. The findings suggested that increasing pollution levels in coastal waters were strongly linked to the spectral indices derived from Sentinel-2 imagery. In addition, the lack of optimal determination of site-specific CHL factor, CHL exponent, TSM factor and TSM exponent components may be one of the other reasons for the low correlation between spectral indices and water quality parameters.

In recent years, deep learning (DL) methods utilizing neural networks have gained considerable research interest in water quality parameter prediction applications, due to their scalability and enhanced performance with large datasets (Ewuzie et al. 2022). The GEE platform offers a range of functions, including image classification using ML algorithms and data visualization. Currently, data-intensive DL models are trained independently of the platform, after which the generated models can be imported and utilized within it (Amani et al. 2020). Directly integrating DL algorithms into the GEE framework could significantly enhance the accuracy and reliability of water quality monitoring, surpassing the capabilities of traditional index-based or machine learning methods.

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