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Impact of COVID-19 on Water Quality of Yamuna River, Delhi

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Abstract:

The surface water bodies are one of the essential sources of water for human activities. Unfortunately, they are under severe stress because of anthropogenic activities, so it is necessary to maintain their quality. This study assesses the Yamuna River's water quality during pre- and post-COVID-19. A model is developed using a combination of measured parameters and satellite image-derived indices to analyze the impact of COVID-19 on the water quality status after a year. Five major water quality parameters (WQPs), such as turbidity, dissolved organic matter (DOM), dissolved oxygen (DO), the potential of hydrogen (pH), and suspended particulate matter (SPM), are considered in this study. The samples were collected from Wazirabad (Ram Ghat) to Okhla barrage (20 locations) from December 2019 to December 2020. The results revealed that the indices derived from remote sensing (RS) data and the in situ data obtained throughout the study had varying degrees of accuracy. Actual DO measurements demonstrated a strong correlation with estimated MNDWI mean values, with an R^2 of 0.27; actual pH concentration demonstrated a strong correlation with estimated GNDVI mean values; actual DOM measurements demonstrated a strong correlation with estimated SWIR_B12 mean values; actual SPM measurements demonstrated a strong correlation with estimated SWIR_B11 mean values, and actual water turbidity measurements demonstrated a strong correlation with estimated normalized difference turbidity index (NDTI) mean values, with an R^2 of 0.34. The research's conclusions support estimating water quality parameters in dry regions using RS data from Sentinel-2.

Keywords: Remote sensing Water quality parameters Yamuna river COVID-19

1. INTRODUCTION

All living things depend on water for their survival and nourishment. Due to the accessibility and abundance, rivers are the most frequently used surface water sources, which has sped up human population growth and development close to watercourses [1]. Rivers have seen considerable environmental challenges due to contamination from heavy agricultural pesticide drainage and sewage from production processes, garbage, and other urban waste sources, especially in developing countries. The Ganga River starts at Saptarishi Kund on the Yamunotri glacial mass in the Himalayas, flows 1376 kilometers to Allahabad, and is the Ganges' largest water contributor. One of the primary Ganga tributaries and source of fresh water, the Yamuna, flows through India's capital city of Delhi. It has recently been regarded as one of India's most polluted rivers. The river's water quality has declined over the last few years as it gets much garbage from homes and farms, hazardous waste contaminants [2], and government releases. The water quality is degrading and becoming unfit for any use due to the water contamination, which is a major cause for concern.

One of the most virulent diseases to have ever afflicted Mankind is thought to be the Novel Coronavirus-driven COVID-19 worldwide pandemic. To stop the spread of the disease, the Indian government has instituted a total lockdown as of midnight on March 24, 2020 [3]. An obvious outcome of the lockdown was improving environmental quality across India's megacities, with work ceasing in factories and industries, the shutdown of commercial establishments, and transportation systems nearly at a standstill [4-6]. The second most evident effect is a potential purging of the country's waterways, particularly those that flow through significant urban areas [7-8]. There has not been much in-depth research on this topic; however, the physical and chemical properties can reveal water characteristics and factors to assess water quality [9].

Water quality indices (WQIs) are among the best ways to describe water quality [10-11]. Because they combine data from a variety of water quality metrics into a single number that can be used to understand water quality overall at various monitoring sites at a given time [12–13] and support strategic planning for water quality management programs through numerical index values [14-15]. Using a modified version of the multicriteria decision-making technique for Order of Preference by Similarity to Ideal Solution, river sections were ranked according to their waterquality by coupling water-quality indicators with the corresponding standards [16]. Research literature indicated GIS techniques for distinguishing the potential zones of water quality using the inverse distance weighting [17-19], an interpolation technique for analyzing the spatial distribution of various physio-chemical parameters. These parameters include Total Solids, Total Dissolved Solids, Total Suspended Solids, Hydrogen Ion Concentration, Chemical Oxygen Demand, Biochemical Oxygen Demand, Dissolved Oxygen, Salinity, Chloride, and Alkalinity (TH) [20-22]. GIS techniques distinguishing the potential zones of drinking water quality for measured GIS-surface variation of water quality at Yamuna river using the kriging interpolation method and the weighted arithmetic index method have been used for calculating WQIs [23]. An integrated approach to measure water quality has been proposed by [24] to analyze 13 physical-chemicals properties using the Canadian Council of Ministers of the Environment Water Quality Index and Weighted Arithmetic Water Quality Index. The water quality of Base, India, has been determined by nine water quality parameters in a study conducted by [25]. GIS with RS was found to be very effective in estimating WQPs.

RS data have the potential to provide knowledge of broad-scale changes and the link between offshore and near-shore waters [26]. For empirical modeling, the authors developed statistical relationships between measured spectral and water quality characteristics. Using principal component analysis, surface water quality is determined by factors such as pH, temperature, electrical conductivity, dissolved oxygen, turbidity, total dissolved solids, salinity, chloride, acidity, total alkalinity, total hardness, nitrate ions, and the total amount of coliform bacteria, in the study conducted by [27]. Based on measurements taken at Palla station in Delhi between 2009 and 2019, [28] analyzed the physio-chemical and biological parameters such as total alkalinity, total dissolved solids, total coliform, and chemical oxygen demand of the Yamuna river. The change in water quality of the river Ganga in terms of total suspended solids and turbidity has been assessed through Landsat-8 multispectral RS data and in situ observations. The authors analyzed the change in spectral reflectance of the water along the river in the visible region [29]. A hybrid machine learning technique, including a relief-based feature selector and decision tree classifier, has been used to predict the water quality of the Yamuna river [30]. The Yamuna River's water quality variables were forecasted by the deep learning-based Bi-LSTM model (DLBL-WQA) [31]. The suggested model demonstrates a novel approach incorporating missing value imputation in the first phase. Feature maps are generated from the input data in the second phase, and a Bi-LSTM architecture is used in the third phase to enhance learning. The training error is minimized by applying an optimal loss function, which helped in a forecasting accuracy improvement. This work aims to construct a linear regression model between WQPs and S2-based spectral bands and Indices for monitoring water quality. Therefore, the best R^2 values and overall accuracy will be the emphasis. Sentinel-2 provides great geographical resolution data that supports identifying these factors using spectral bands and indices. The current study uses regression analysis to identify the connection between the estimated and real water quality indicators.

The rest of the paper is organized as follows: section two presents materials and methodology, section three gives results and discussion, and section five concludes the paper.

2. MATERIALS AND METHODS

2.1 Study Area

The water samples were collected at equivocal distances, incorporating 20 unique places covering 21 km from Wazirabad to Okhla Barrage, Delhi (Fig. 1). The samples were collected in the corrosive washed polyethylene before and after 12 months of COVID-19. The samples are analyzed based on the following properties turbidity, DOM, SPM, pH, and DO. In Delhi, the average annual rainfall is 714 mm, with three-quarters of that falling in July, August, and September. Temperatures can reach 40-45 °C in the summer, and winters are usually cold, with temperatures dropping to 4 to 5 °C in December and January.

2.2 Water Sample Collection and Lab Testing

Water samples were collected monthly from the site from December 2019 to December 2020, using a 2L container. The sampling containers were washed carefully before sampling to remove any type of solids or impurities. The sample temperatures were recorded and collected well away from the edges of the water body. All the experiments were carried out as per the method specified in standard methods [32].

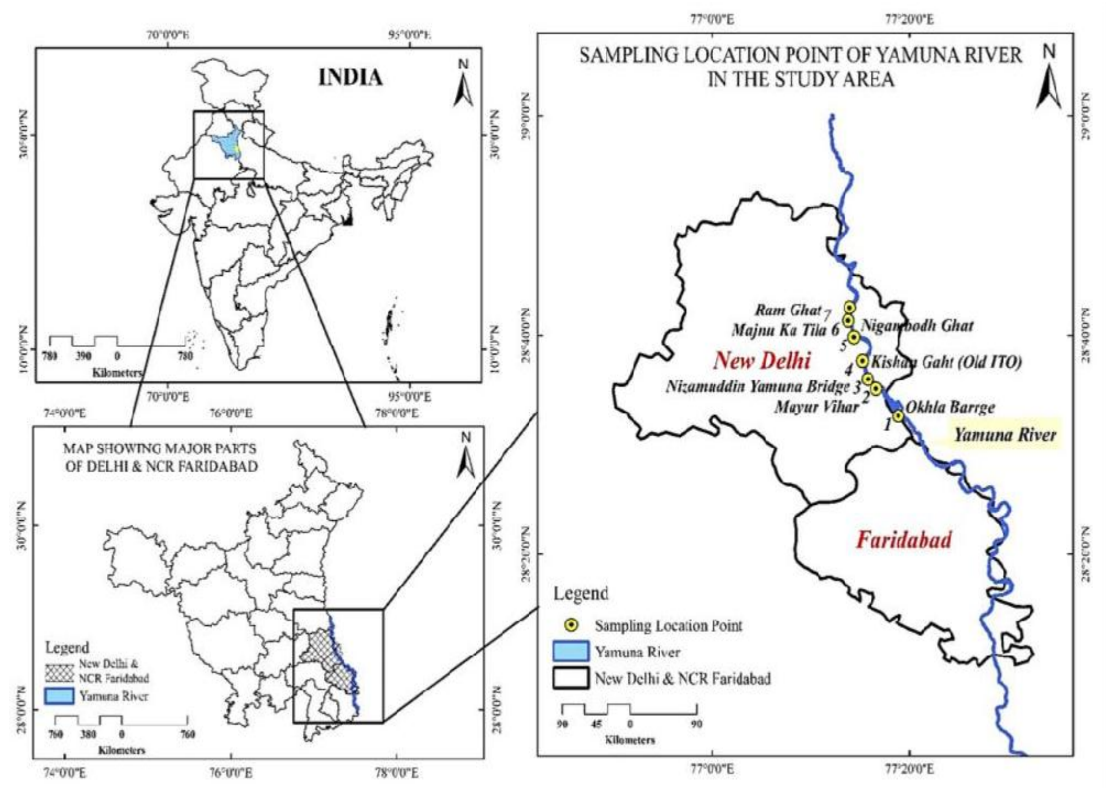


Fig. 1. The AOI indicates Yamuna River and in situ survey locations.

2.3 Remote Sensing Data

Spectral bands from Sentinel-2 were obtained from the Copernicus open access hub. These images were acquired and preprocessed between December 2019 and December 2020 to convert pixel values to reflectance. This time frame represents the first corona wave's pre- lockdown and post-lockdown stages. Consequently, 11 images (One month each) were collected and used to build a correlation and regression model utilizing in-situ data. Due to a high amount of cloud cover, suitable images for August and September 2020 could not be taken. The vegetation indices and raw bands used for correlating with water quality metrics are shown in Table 1 and 2 respectively. Modified normalized difference water index (MNDWI), green normalized difference vegetation index (GNDVI), and NDTI are three separate remotely sensed indices that were obtained to reflect three different water quality factors.

Table 1. List of Sentinel 2 vegetation indices used in this study

Index	Vegetation Index Formula	Reference
GNDVI	$\left(\frac{\rho_{nir} - \rho_{green}}{\rho_{nir} + \rho_{green}}\right)$	[33]
NDTI	$\left(\frac{\rho_{red} - \rho_{green}}{\rho_{red} + \rho_{green}}\right)$	[34]
MNDWI	$\left(\frac{\rho_{green} - \rho_{swir}}{\rho_{green} + \rho_{swir}}\right)$	[35]

Table 2. List of Sentinel 2 bands used in this study

Sentinel 2A	Bands	Central Wavelength (nm)	Wavelength Range (um)	Band-Width (nm)	Spatial resolution (m)
B2	Blue	490	0.439-0.535	0.096	10
B3	Green	560	0.537-0.582	0.045	10
B4	Red	665	0.646-0.685	0.039	10
B8	NIR	842	0.767-0.908	0.141	10
B11	SWIR_B11	1610	1.539-1.681	0.142	20
B12	SWIR_B12	2190	2.100-2.280	0.180	20

Correlations between the water quality index and S2 spectral bands:

Water quality data were analyzed for WQPs for nine monitoring sites. Data received in December 2019 was used to represent the situation before the lockdown period, while data obtained in December 2020 was used to represent the situation following the lockdown phase. For the same period as the river dataset, the Delhi Pollution Control Committee was also used to obtain information about the water quality status of the 20 drains in Delhi that run into the Yamuna. This research was investigated to determine the effluent quality flowing into the river and whether the lockdown had any other effects besides those on the main waterway on the area's drains. As few indices are sensitive to water bodies, such as MNDWI and NDTI were utilized for correlating with the WQPs.

2.4 Flow of the methodology

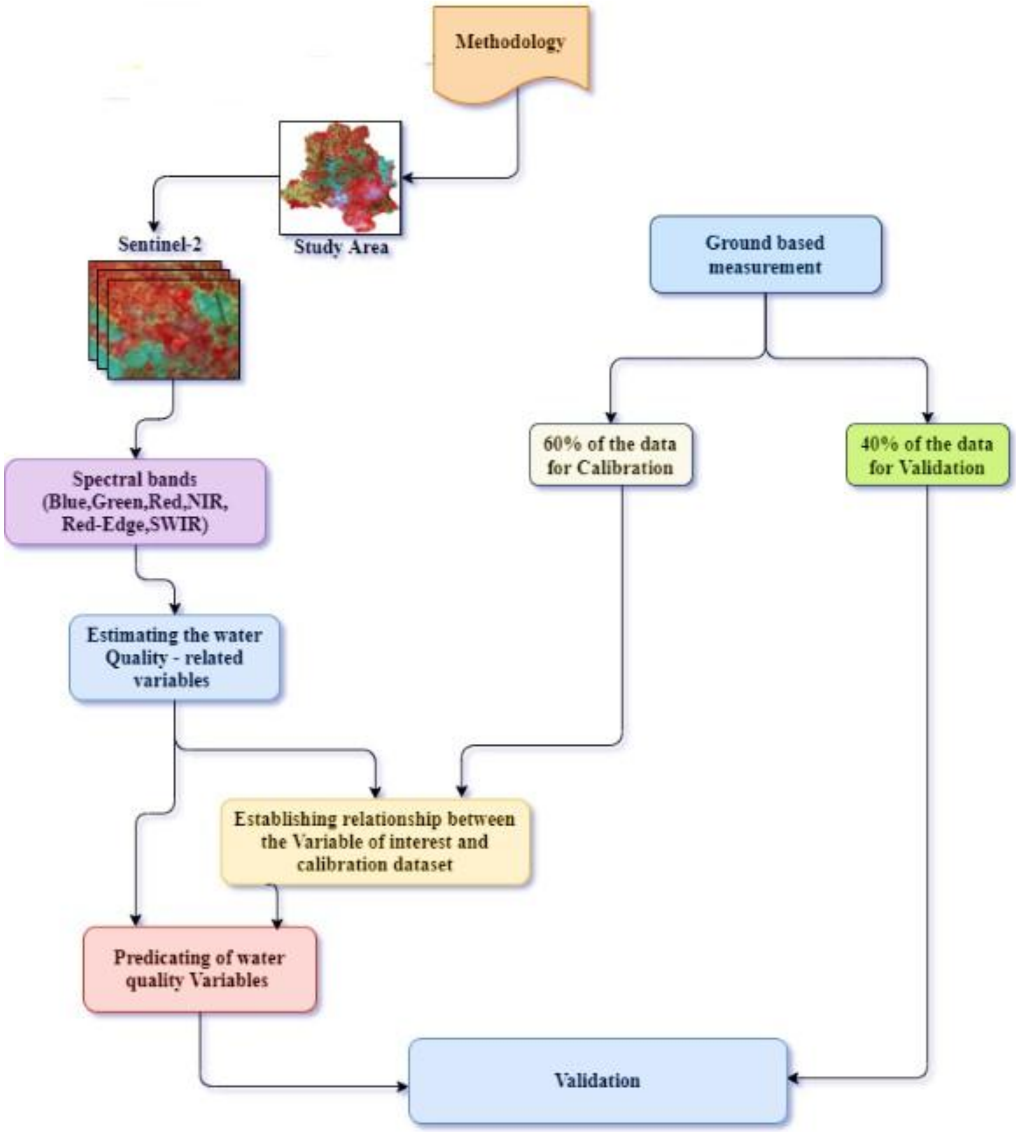


Figure 2. Flow chart of the research methodology

3. RESULT AND DISCUSSION

First, a correlation matrix was developed to understand the variability between the spectral bands and WQPs. After that, a linear regression was established between correlated S2 bands and indices with WQPs, followed by the accuracy assessment and conclusions.

3.1 Correlation matrix of water quality parameters, indices, and reflectance SWIR bands

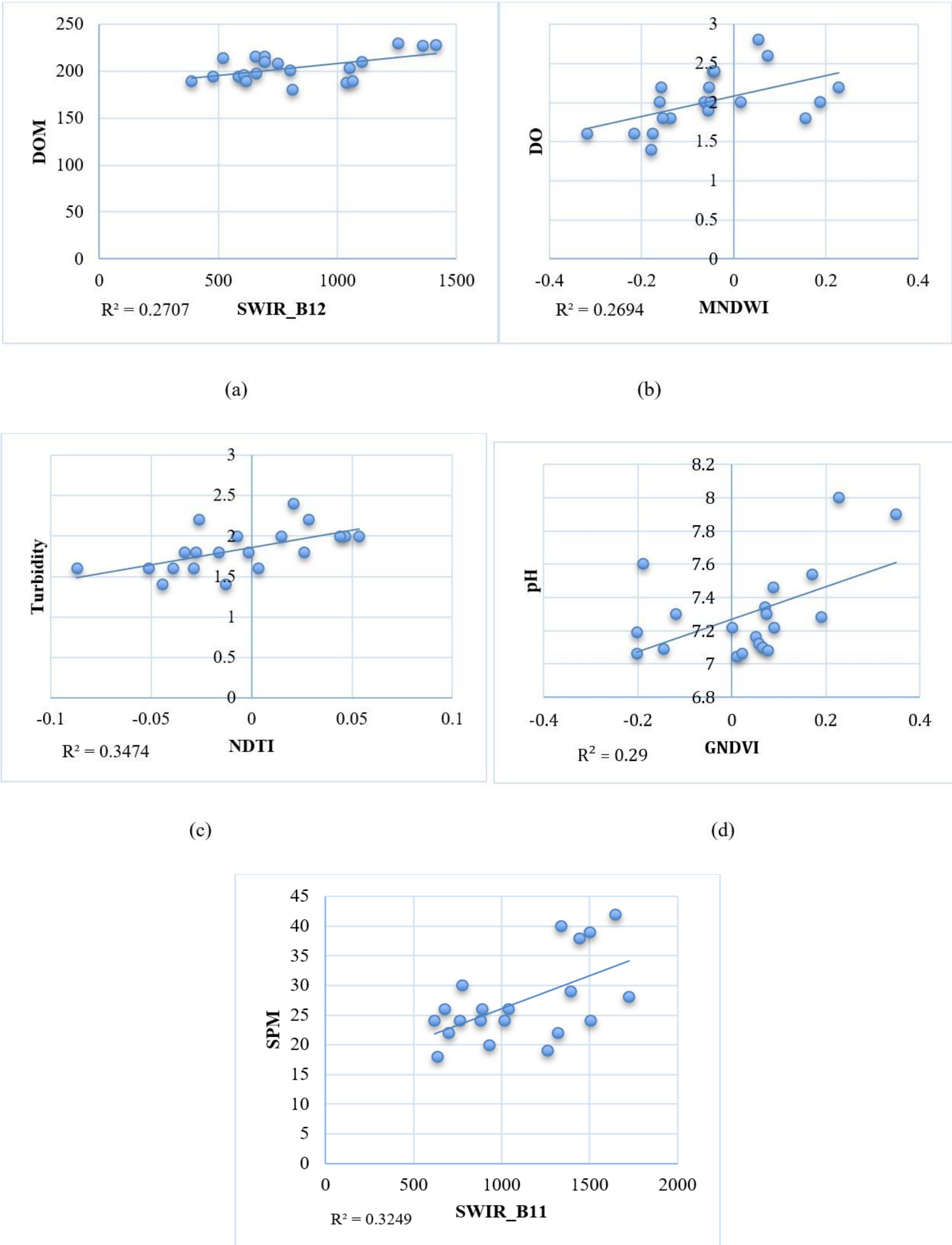
Correlations were determined on cumulatively collected parameters to understand the variability within the WQPs. Fig. 3 indicates the correlation between WQPs and sentinel-2-based spectral bands and indices. A good correlation between MNDWI with DO can be observed in Fig. 3.

	PH	Turbidity	SPM	DOM	DO	NDTI	MNDWI	GNDVI	SWIR_B11	SWIR_B12
PH	1									
Turbidity	0.417	1								
SPM	-0.114	0.456	1							
DOM	0.0009	0.523	0.728	1						
DO	0.4	0.137	-0.485	-0.2212	1					
NDTI	0.194	0.225	0.0139	-0.1105	0.143	1				
MNDWI	-0.0185	0.255	0.5986	0.7674	-0.2174	0.2473	1			
GNDVI	0.0114	-0.255	-0.5627	-0.7804	0.1561	-0.2178	-0.9876	1		
SWIR_B11	-0.241	-0.28	-0.1646	-0.358	-0.1802	-0.5087	-0.584	0.5859	1	
SWIR_B12	-0.1	-0.175	0.0475	-0.1707	-0.2845	-0.3383	-0.3303	0.3344	0.7649	1

Figure 3. Correlation matrix of WQPs and RS based spectral bands and indices

3.2 WQPs modeling using linear regression

To assess and realize the consistent correlations between the actual WQPs concentrations gathered on-site and the corresponding WQPs in reflectance values calculated from remote sensing data, linear regression analyses were used. There was no time gap between the in-situ sampling and the RS data acquisition because both the sentinel-2 data acquisition and the in-situ water quality parameters were carried out on the same day. The average, linear and nonlinear regressions were calculated as part of the statistical analyses. The power of the link between the two variables was examined using R^2 analysis. A t-test was used to determine whether a significance level was significant (p 0.05) or not significant ($p > 0.05$), indicating that there was a link between the two variables. To assess the analysis consistency of linear and nonlinear regressions, statistical analyses were conducted using the mean values of ground measurements compared to the statistical values of RS data. A significant association between the variables was defined as a p-value of 0.05 or less, and an absence of a significant association as one with a p-value of more than 0.05. The linear regression analysis of the variables DOM, DO, turbidity, pH, and SPM with GNDVI and NDTI, respectively, is shown in Fig. 4. In each tested water quality measure (SWIR B11, SWIR B12, MNDWI, GNDVI, and NDTI), the linear regression model's findings indicated that mean pixel values were the best for demonstrating a coherent link between the WQPs and the remotely sensed estimated ones. Based on the summary of the fit analysis [36-37] (Fig. 4), the R^2 reported in Table 3 demonstrates the strong correlation between the mean value of the in-situ water quality measurements and the conducted values from RS data.



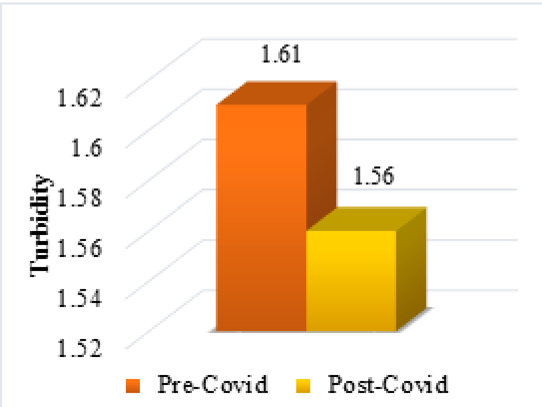
(a) (b) (c) (d) (e)

Figure 4 The linear regression model (a) DOM vs SWIR_12, (b) MNDWI vs DO, (c) Turbidity vs NDTI (d) pH vs GNDVI (e) SPM vs SWIR_B11.

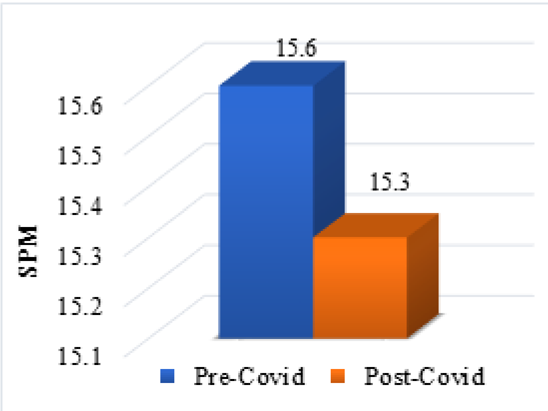
Table 3. Accuracy of the correlated regression model

Sl No.	Predicted Water Quality Parameters	Overall Accuracy	R^2
1	DOM	51	0.27
2	DO	60	0.26
3	pH	48	0.29
4	Turbidity	55	0.34
5	SPM	70	0.32

Four distinct zonal statistic types underwent regression analysis between the WQPs concentration and the calculated spectral bands and indices. The DO in the dam lake has decreased (Fig. 5), indicating less pollution impact on the water quality on the watershed scale [38,39]. Carpenter [40] first investigated water turbidity as an indication of sedimentation processes using data from the Landsat TM sensor images. As a result, the method was created to consider modifying the current sensors' center bandwidth, as Doxaran [41] reported utilizing (SPOT) images. Particularly in inland water, the duality of the bands at SWIR_B11 and SWIR_B12 for suspended particulate matter and DO prove useful in detecting turbidity [42]. Sentinel-2's core band wavelengths in the near-infrared range also cover the approved bands for suspended particle detection, enabling the sensor to estimate water turbidity with high precision.



(a)



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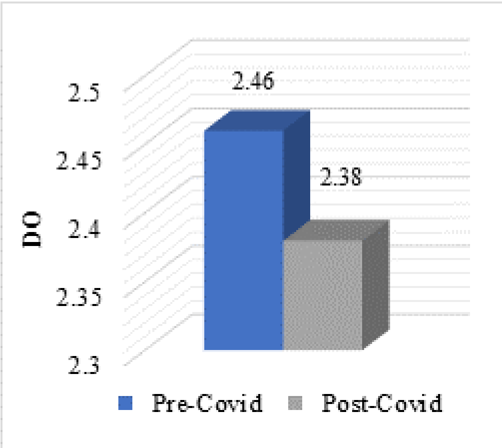
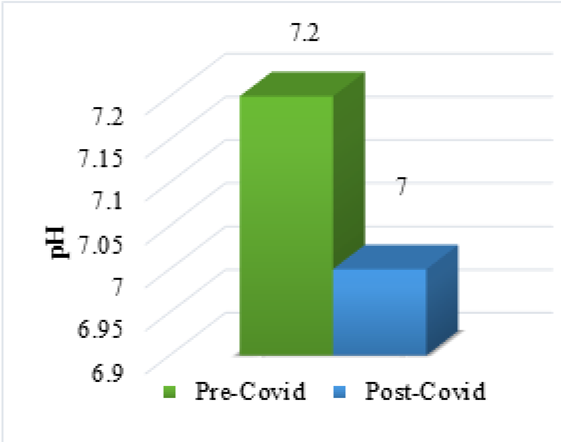
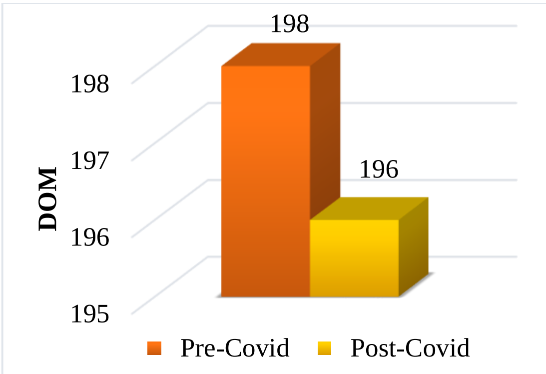


(c)



(d)



(e)

Figure 5. Pre and post COVID-19 changes in (a) Turbidity (b) SPM (c) DO (d) pH (e) DOM

4. CONCLUSIONS

Costly laboratory materials and ongoing labor are needed to monitor water quality indicators. The applied approaches and thorough evaluations provided answers to the issues surrounding the viability of estimating the defined water quality parameters utilizing a linear empirical approach across temporal remote sensing data. Sentinel-2 remote sensing data were effectively used to estimate dissolved oxygen, dissolved organic matter, pH, suspended particle matter, and water turbidity. Sentinel- 2's SWIR_B11 and SWIR_12 bands are the sensor's important characteristics for accurately calculating the targeted water quality metrics. Additionally, there was a strong connection between the mean values of the raster data and the actual data from the performed laboratory exams.

Conflicts of Interest: The authors declare no conflict of interest.

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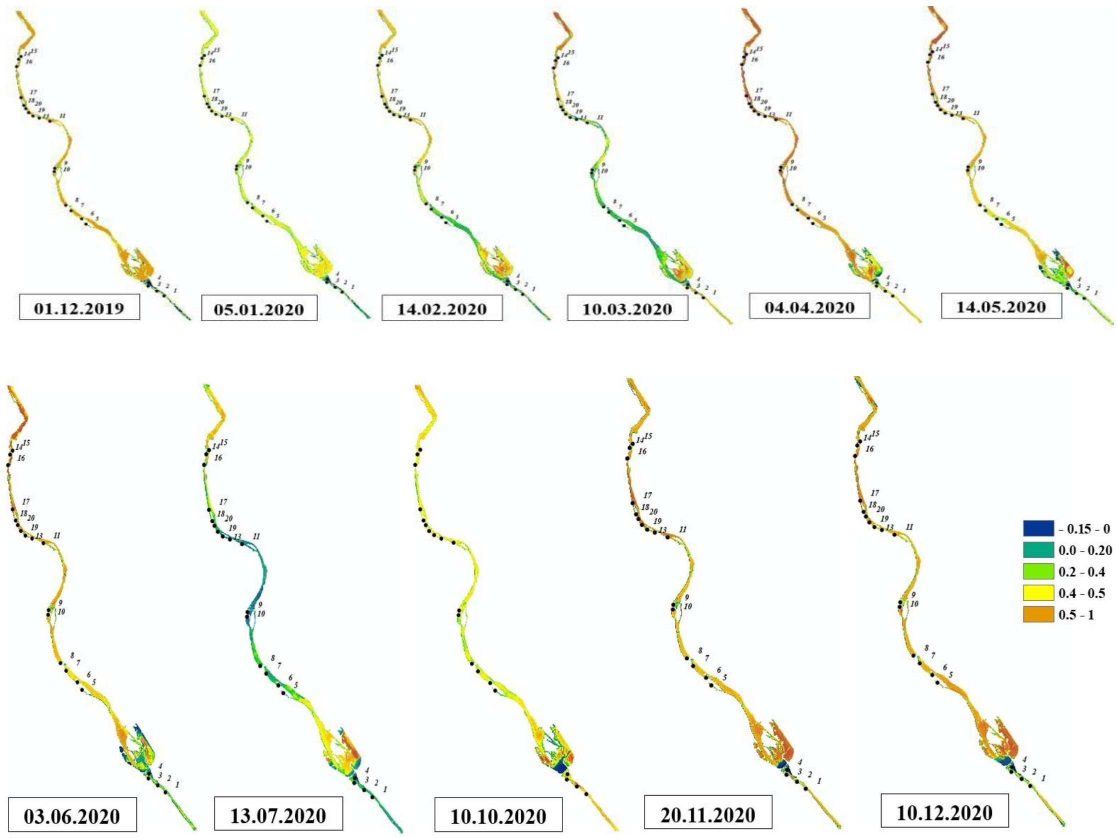
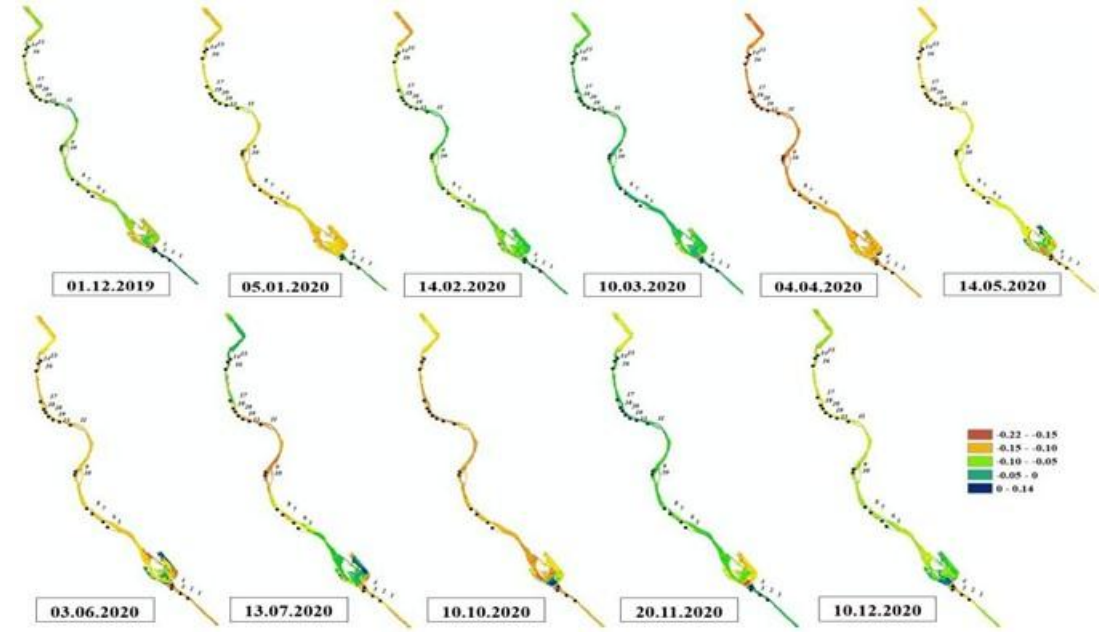
Appendix-1

MNDWI



NDTI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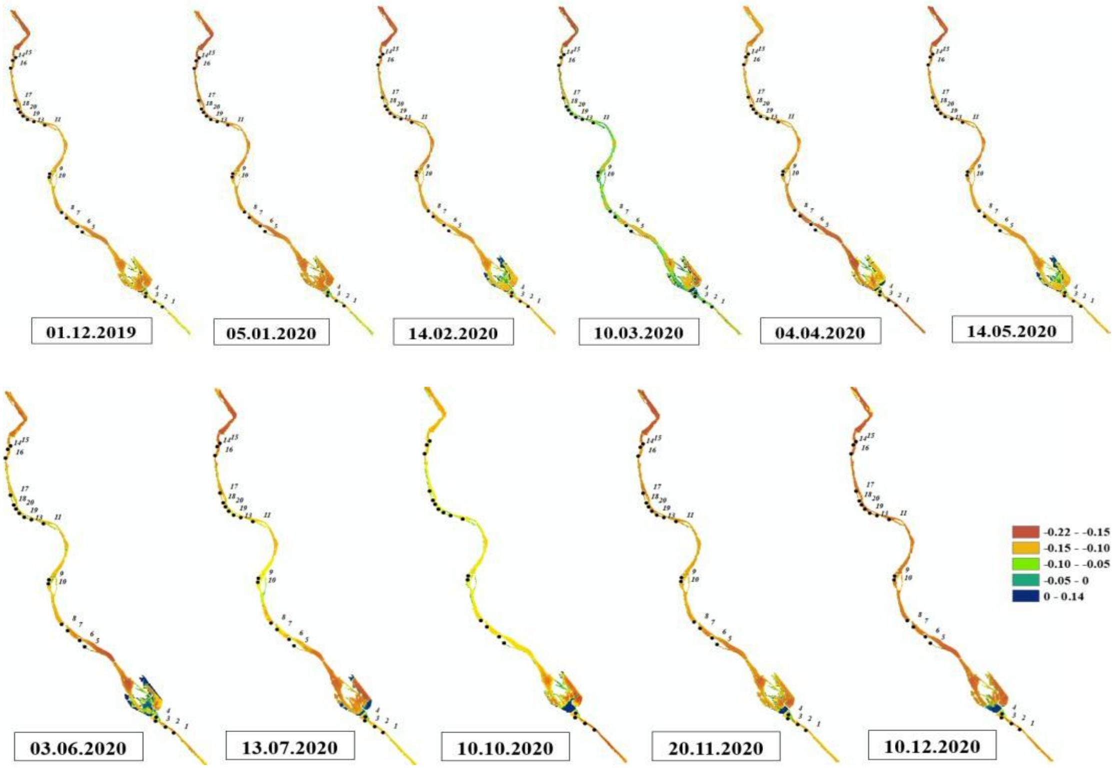
13.07.2020
10.10.2020
20.11.2020
10.12.2020
-0.22 - -0.15
-0.15 - -0.10
-0.10 - -0.05
-0.05 - 0
0 - 0.14

GNDVI


01.12.2019
05.01.2020
14.02.2020
10.03.2020
04.04.2020
14.05.2020
03.06.2020
13.07.2020
10.10.2020
20.11.2020
10.12.2020
-0.22 - -0.15
-0.15 - -0.10
-0.10 - -0.05
-0.05 - 0
0 - 0.14