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RESEARCH ARTICLE

Assessing lake water quality during COVID-19 era using geospatial techniques and artificial neural network model

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Abstract

The present study evaluates the impact of the COVID-19 lockdown on the water quality of a tropical lake (East Kolkata Wetland or EKW, India) along with seasonal change using Landsat 8 and 9 images of the Google Earth Engine (GEE) cloud computing platform. The research focuses on detecting, monitoring, and predicting water quality in the EKW region using eight parameters—normalized suspended material index (NSMI), suspended particular matter (SPM), total phosphorus (TP), electrical conductivity (EC), chlorophyll-α, floating algae index (FAI), turbidity, Secchi disk depth (SDD), and two water quality indices such as Carlson tropic state index (CTSI) and entropy-weighted water quality index (EWQI). The results demonstrate that SPM, turbidity, EC, TP, and SDD improved while the FAI and chlorophyll-α increased during the lockdown period due to the stagnation of water as well as a reduction in industrial and anthropogenic pollution. Moreover, the prediction of EWQI using an artificial neural network indicates that the overall water quality will improve more if the lockdown period is sustained for another 3 years. The outcomes of the study will help the stakeholders develop effective regulations and strategies for the timely restoration of lake water quality.

Keywords COVID-19 lockdown · Google Earth Engine · Suspended particulate matter · Chlorophyll-α · Water quality · East Kolkata Wetlands

Introduction

A new strain of coronavirus emerged from Wuhan, China, in December 2019. The World Health Organization (WHO) named it coronavirus disease 2019 (COVID-19) which rapidly spread to the whole world within a few months, causing devastating effects on both human life and the economy (Wang et al. 2020). As a result, WHO declared it a pandemic, and with no medications available, many countries started restricting the movement of people, transport, and social interactions in the form of lockdowns to avert the spread of the infection (Figueiredo et al. 2020). The worldwide COVID-19 lockdown characterized by the closure of production sectors, and minimal anthropogenic activity, caused a great impact on environmental quality especially the air (Liu et al. 2021; Filonchyk et al. 2021; Mor et al. 2021; Jion et al. 2023) and surface water (Kour et al. 2021; Liu et al. 2021; Qiao et al. 2021; Jawad-Ul-Haque et al. 2023). For example, Tokatli and Varol (2021) observed that the water quality of the Ergene River (Turkey) was significantly improved in terms of the concentration of Ni, Zn, Cu, As, Pb, and Cd. Moreover, they observed that the values of carcinogenic risk of As and Cr had been reduced by 60% and 94%, respectively, as an effect of the lockdown. Braga et al. (2020) identified the improvement in water transparency of Venice Lagoon in Italy. Chen et al. (2021) observed the positive impact of the COVID-19 lockdown on the ecological environment of the Haihe River. They estimated a decrease in turbidity of 219.06% during the lockdown. As the lockdown was imposed, normal life comes to pause resulting in logistic and legal problems in collecting data to know about the quality lockdown.

Therefore, water quality monitoring, mapping, and predicting depend greatly on the geospatial data sources. The majority of the works produced on water quality are

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thus satellite data-driven and simulated using geospatial modeling (Said and Khan 2021; Dandge and Patil 2022). Improved water quality as an effect of the COVID-19 lockdown has been observed for many inland waterbodies in India. For example, the improved water quality in terms of BOD, COD, and DO concentration was identified for the Ganga (Dutta et al. 2020) and Yamuna River (Arif et al. 2020). Besides, Aman et al. (2020) illustrated a 36% reduction in suspended particulate matter (SPM) in the Sabarmati River in response to reduced anthropogenic activities during the lockdown. A similar finding that there is a 15% reduction in SMP in the Vembanad Lake was identified by Yunus et al. (2020). Chakraborty et al. (2021) observed improved water quality in the Damodar River in terms of the modified water quality index and improved nutrient status in terms of the trophic state index. Moreover, they observed that potential ecological risk declined by 63% in the Damodar River during the lockdown.

The Ramsar Convention recognizes the East Kolkata Wetlands (EKW) as a wetland of international importance in 2003. EKW receives a huge amount of untreated, municipal, and industrial wastewater. Therefore, many researchers have investigated wetlands from the perspective of ecosystem vulnerability due to fragmentation, pollution (Roy-Basu et al. 2020), and conversion (Ghosh and Das 2020). In India, to prevent the outbreak of COVID-19, a nationwide lockdown was announced first 24th March 2020 and imposed till 31st May 2020. Afterward, the nation witnessed a series of complete lockdowns. During this situation, many inland waterbodies have received a significantly lower amount of waste which has a corresponding effect on water quality. The water quality and ecosystem health of EKW are also supposed to be changed in response to a series of complete lockdowns. EKW is a highly significant wetland that sustains society as well as extensive economic activity and biological variety within its catchment region. However, there has been no previous systematic assessment of COVID-19 lockdown effects on EKW lake water quality, nutrient status, and future scenarios of water quality impact on the aquatic environment of EKW.

Furthermore, the present study employed a cloud-based platform, such as Google Earth Engine (GEE), because of its multi-petabyte data catalog that is ready for assessment, and high-performance computing capabilities that may be used for a wide range of rising social challenges including environmental preservation. Therefore, this cloud-based platform is gaining much popularity among scientific researchers. Kwong et al. (2022) and Zlinszky et al. (2017) studied the water quality parameters on the GEE platform for extensive geospatial assessment and easy accessibility to freely available data and robust computing capabilities. Again, to analyze the surface water quality, Khan et al. 2021 have adopted this cloud-computing technique for its several benefits and especially for the easy access to atmospherically corrected satellite imagery. Most of the researchers have investigated various water quality parameters in their study mostly because the platform does not necessitate downloading large satellite images while reducing the downloading time and storage capacity (Kislik et al. 2022; Bioresita et al. 2021; Amani et al. 2020). Despite performing several types of research on water quality metrics, there has been no previous systematic assessment of COVID-19 lockdown effects on EKW lake water quality, and nutrient status. In addition, to the best of our knowledge, this is the first research to simulate the entropy-weighted water quality index (EWQI) to better understand the water quality if the lockdown is continued for the next 3 years. Hence, this study focuses to attribute this research gap by investigating the water quality metrics and associated simulation by implementing laboratory-based analysis coupled with geospatial and cloud-computing techniques. Therefore, this research aims to ascertain the water quality, nutrient content, and ecological risk of the EKW regions using several parameters and indices in the pre-lockdown (2019), lockdown period (2020), and post-lockdown (2021) periods for the pre-monsoon, monsoon, and post-monsoon seasons. Additionally, this study will simulate the entropy-weighted water quality index (EWQI) to monitor the conditional short-term changes.

Materials and methods

Study area

East Kolkata Wetlands (EKW) is an important peri-urban ecosystem situated on the eastern fringe of Kolkata megacity, having an area of ~ 125 km^2 and extending from 22°25′00″N to 22°35′00″N latitude and 88°20′00″E to 88°35′00″E longitude (Sahu and Sikdar 2008). Administratively the wetland covers 37 mouzas (smallest administrative units for revenue collection in India) of two districts (North and South Twenty-Four Parganas) and the Kolkata municipal corporation (KMC). Out of the entire wetland area, 58.52 km^2 consists of waterbodies followed by agricultural land (47.18 km^2), productive farming area (6.02 km^2), and urban area (13.26 km^2). The wetland ecosystem of EKW is very complex from the perspectives of geomorphic evolution, diversity in living species, dynamics in ecosystem functions, etc. EKW is also known as a sewage-fed wetland that receives ~ 600 million liters of sewage per day from KMC (Roy-Basu et al. 2020). Besides, the wetland having 364 sewage-fed ponds is also used for pisciculture, producing 10,500 MT of fish every year (Vicziany et al. 2017). However, the ecosystem of EKW has become highly vulnerable to fragmentation, loss of wetland area, and water pollution due to its proximate location to KMC (Ghosh and Das 2020).

Therefore, the ecosystem services, i.e., gas regulation, land surface temperature control, nutrients and sediment retention, flood control, habitats for diversified living species, primary production, recreation, and ecotourism, provided by EKW are degrading significantly.

Data sources

Geospatial data

The geospatial data used for the current study are Landsat 8 OLI and Landsat 9 for the years 2019, 2020, and 2021, with the three seasons, i.e., pre-monsoon, monsoon, and post-monsoon, taken into account for each year. All the Landsat data are available on the GEE web platform as surface reflectance and top-of-atmosphere (TOA) corrected reflectance. Therefore, the present study considers the "Landsat 8 surface reflectance tier 1," which provides the atmospherically corrected surface reflectance from the Landsat 8 OLI/TIRS and Landsat 9 sensors. The Landsat image, which covers the entire East Kolkata Wetland area, is referenced as 138 path and 44-row number as per the world reference system (WRS) which is used for Landsat products. The details of the Landsat 8–9 and acquisition date have been presented in Table 1.

Water quality data

For the present investigations, water quality data have been collected/extracted from two major sources—(1) geospatial data (secondary data) and (2) field data (primary data). Eight water quality parameters derived from the satellite images are (1) chlorophyll-α (Chl-α), (2) turbidity, (3) SPM, (4) EC, (5) TP, (6) NSMI, (7) FAI, and (8) SDD. Moreover, a total of 60 water samples (2018–2019) have been collected from 5 monitoring stations of EKW (Fig. 1). Among the total water quality samples ($n = 60$), each of the 20 samples was collected for pre-monsoon, monsoon, and post-monsoon seasons. Field data from 2018 to 2019 was acquired and suitable tests as per the guidelines of the American Public Health Association (APHA) Standard as mentioned in Table 2.

Methods

Geospatial data processing and water quality indices

Based on NDWI and mNDWI techniques, the waterbody area of EKW was derived from the Landsat 8 images. Additionally, the individual parameter and indices related to water quality have been derived and assessed for EKW. TSS was measured following normalized suspended material index (NSMI) as used by Hossain et al. (2010). The techniques of Wang et al. (2021) and Lin et al. (2004) were used to measure the water's turbidity, while the algorithm of Mushtaq and Nee Lala (2017) was used to measure the EC. The estimation of Chl-α, TP, and SDD was done following the techniques of Diédhiou et al. (2019), Su and Lo (2021), and Bonansea et al. (2019) respectively for developing the CTSI, an important indicator of ecosystem health. Besides, FAI for detecting algal blooms in lake water and SMI for measuring suspended sediment amounts in water were derived following Hu (2009) and Nechad et al. (2010), respectively. Finally, entropy-weighted water quality index (EWQI) was computed for assessing the overall water quality of the EKW. The specification of how each individual parameter and water quality indices were derived has been mentioned in a separate supplemental material (SS1).

Table 1 Landsat 8 OLI and Landsat 9 images (path 138–row 44) of the EKW used in this study

Description of bands used	Wavelength (μm)	Bands used to derive parameters/indices	Phases of lockdown	Seasons	Date of acquisition
Band 2—(blue) surface reflectance	0.452–0.512	NSMI = bands 2, 3, 4 Chl(α) = bands 2, 3, 4, 5 Turbidity = bands 2, 3, 4 SDD = bands 2, 3, 5 NDWI = band 3 mNDWI = bands 3, 6 SPM = band 4 EC = band 4 FAI = bands 4, 6 TP = band 4	Pre-lockdown	Pre-monsoon	15 Feb 2019
				Monsoon	26 Aug 2019
Band 3—(green) surface reflectance	0.533–0.590			Post-monsoon	30 Nov 2019
			Lockdown	Pre-monsoon	02 Feb 2020
Band 4—(red) surface reflectance	0.636–0.673			Monsoon	27 Jul 2020
				Post-monsoon	16 Nov 2020
			Post-lockdown	Pre-monsoon	04 Feb 2021
Band 5—(near infrared) surface reflectance	0.851–0.879			Monsoon	31 Aug 2021
				Post-monsoon	02 Nov 2021
Band 6—(shortwave infrared 1) surface reflectance	1.566–1.651				

Bands 1 and 7 were not used to derive the parameters and indices. The details of the equations to derive the parameters and indices have been mentioned in the supplementary materials (SS1)

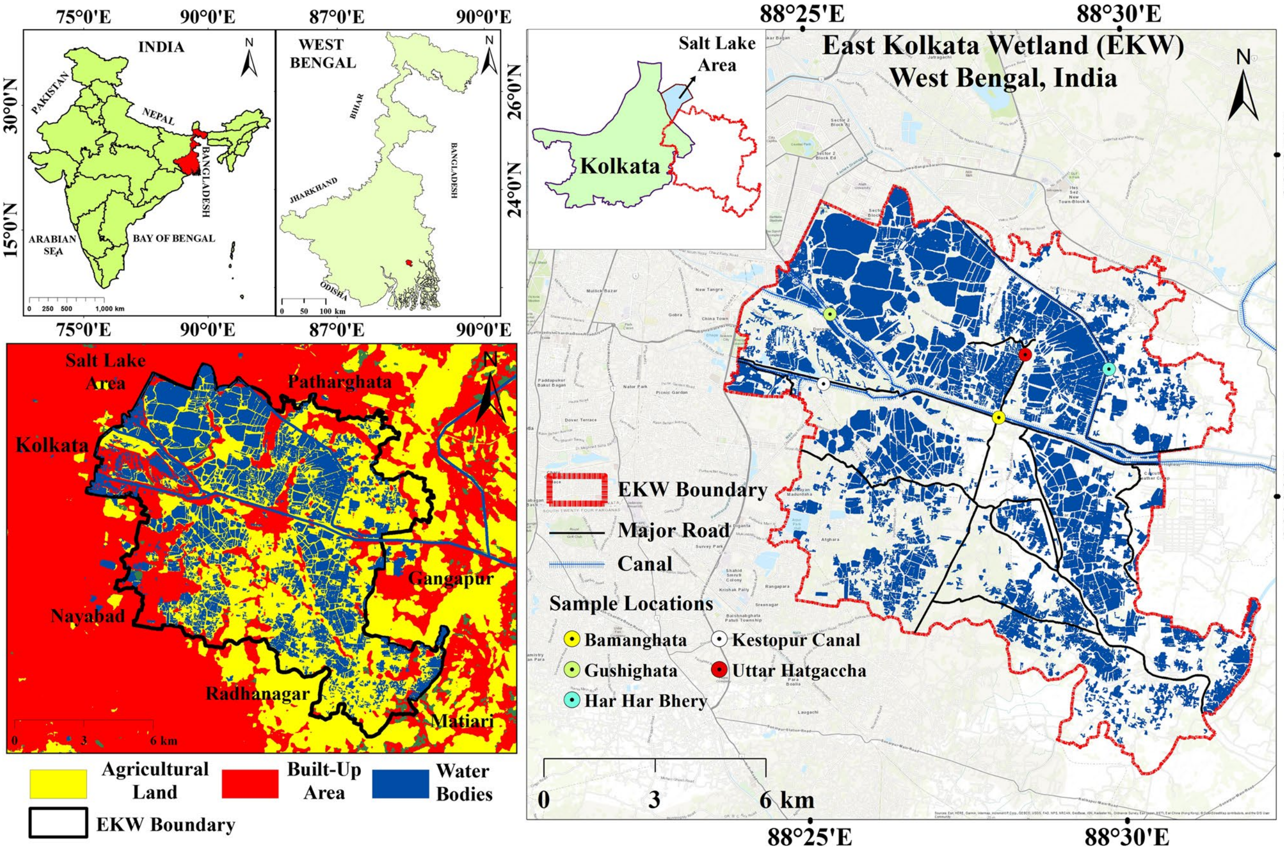


Fig. 1 Location of the study area

Table 2 Water testing methods after APHA

Parameters	Method
Electrical conductivity (μS/cm)	APHA Standard Methods 2510B (2012), 22th edition
Turbidity (NTU)	APHA Standard Methods 2130B (2012), 22th edition
Total suspended solid (mg/l)	APHA Standard Methods 2540D (2012)
Total phosphorus (mg/l)	APHA Standard Methods 4500- P B, 3030 K (digestion), and 4500- P D (determination) (2012)

Source: Annual report 2019–2020, East Kolkata Wetlands Management Authority

Artificial neural networks

In this research, we have employed before-lockdown, lockdown, and post-lockdown data as input in the ANN model to predict the water quality for the next 3 years (Fig. 2). An artificial neural network (ANN) is a computational learning system that is made up of single-neuron structures and linked in a certain way (ASCE 2000) that is specified by their architecture, just like their biological model. NARX is a time-series analysis tool that combines a neural network and a linear ARX model (autoregressive model with exogenous input) (Beale et al. 2017). In this scenario, the neural network is employed to enable the ARX structure to capture nonlinearities (Di Nunno and Granata 2020). NARX is superior to conventional recurrent networks regarding generalization ability (Desouky and Abdelkhalik 2019), which is because NARX can store information two to three times longer than ordinary RNN (Guzman et al. 2017).

Moreover, when compared to other ANN models such as the forward neural network model, the NARX model is a time series model that is used to predict stationary time series (Fig. 3). Since the EWQI parameters look like time series, the NARX model is a good choice for predicting the EWQI. In the NARX model, Levenberg–Marquardt (LM) has been used as training algorithm which follows a Hessian matrix approximation (Bishop 1995), which is expressed using Eq. 1.

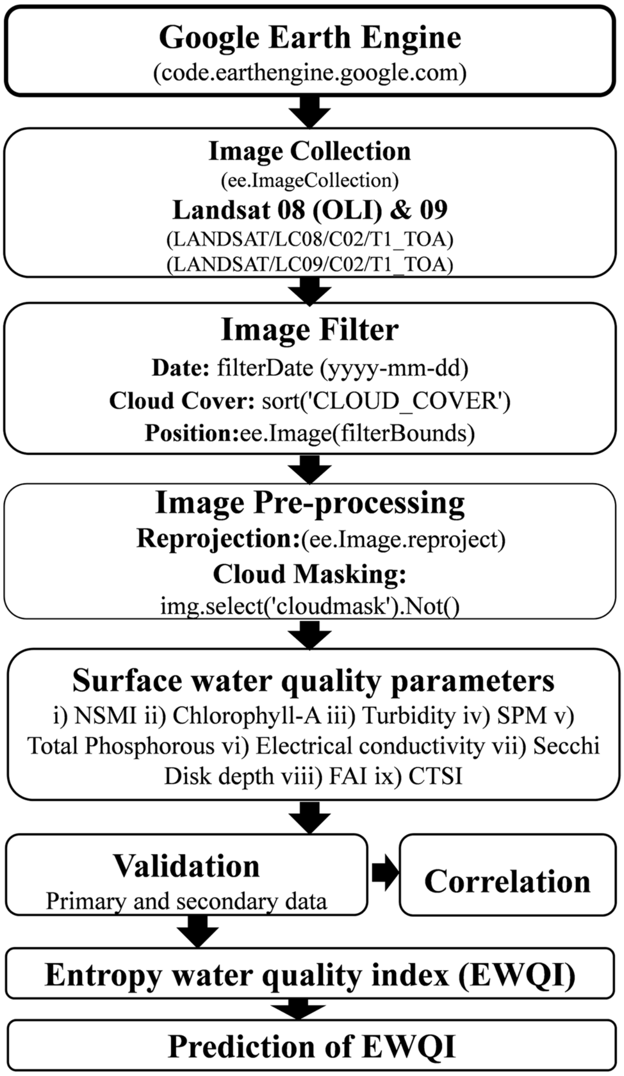


Fig. 2 A systematic framework to estimate the impact of the COVID-19 lockdown on the water quality of East Kolkata Wetland

$$\Delta\omega = \left[J^T(\omega)J(\omega) + \lambda I\right]^{-1} J^T(\omega)e(\omega) \quad (1)$$

ω denotes the weights, J represents the Jacobian matrix, J^T indicates the transpose matrix of J, and J^TJ is the Hessian matrix. "I" stands for the learning matrix, and λ and e are the learning coefficient and vector of network errors, respectively. The parameter λ is automatically updated based on the error at each iteration to secure the convergence. Following the principle of weight optimization of ANN (e.g., Alizadeh et al. 2017), we used a random value of λ to initiate the iteration process for optimizing weights with the LM algorithm. Moreover, the performance of the model prediction is assessed using two well-known statistical methods—the coefficient of determination (R^2) and mean squared errors (MSE) (Chicco et al. 2021; Khan et al. 2021). R^2 is a linear regression method for determining the best fit between measured and model-predicted values, as mentioned in Eq. 2.

$$R^2 = \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}_i\right)^2} \quad (2)$$

y and $\hat{y}$ denote the measured and predicted values, respectively, y stands for the average of measured values, and n equals the number of values. The MSE determines the mean squared difference between measured and predicted values (Eq. 3).

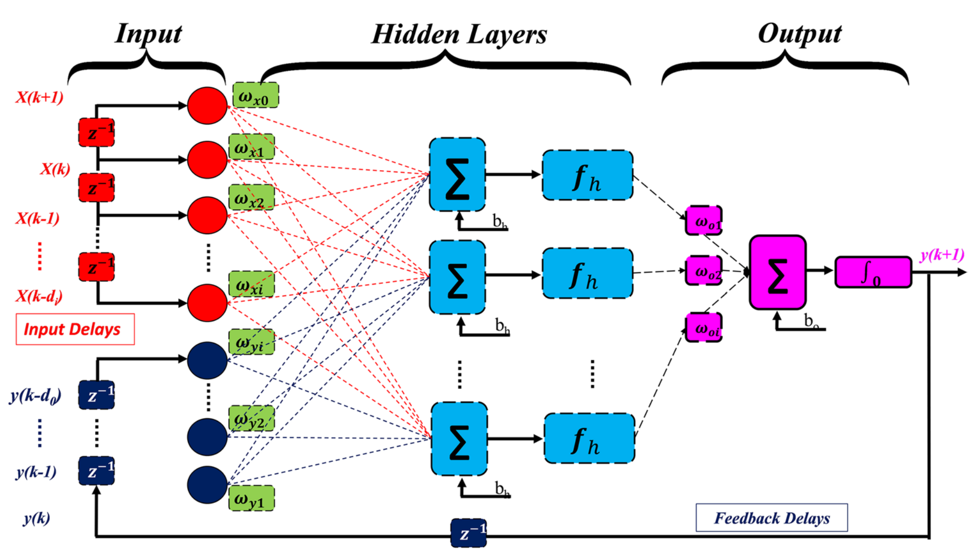
$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \quad (3)$$

Results

Water quality assessment

A total of 8 parameters and 2 indices have been studied for three different seasons—pre-monsoon, monsoon, and

Fig. 3 The architecture of the NARX neural network



post-monsoon of 2019, 2020, and 2021 in this study. The derived results related to the spatio-temporal distribution of these indices in the EKW region are quite significant in terms of judging the status of water quality and its changes that corresponds to the impact of the COVID-19 lockdown in the wetland's catchment area.

Water quality parameters

Regarding NSMI a significant change has been observed between the pre-COVID period (2019) and the COVID-19 lockdown period (2020). In 2019 and 2021, the cleanliness of the lake water was found to decrease in the monsoon period compared to the respective pre-monsoon periods. Contrarily, in 2020, the cleanliness of lake water had increased significantly in the monsoon period compared to its pre-monsoonal magnitude. From late March 2020 to late June 2020, a complete lockdown was preceded by partial lockdowns and containment areas roughly till the end of the year. It possibly had a significant impact on reducing the infusion of suspended materials in the lake water. NSMI values greater than 0.6 experienced a relative increase in its concentrated area being 69.77% in 2020, compared to 77.81% and more than 2000% in 2019 and 2021 of the total wetland area, respectively, between the pre-monsoon and monsoon periods. The areal occupancy of the higher classes of NSMI in the monsoon period of 2020 was also lower compared to 2019 and 2021. NSMI range of 0.51 to 0.6 was observed occupying 7.737 km^2 in 2020 compared to 20.727 km^2 in 2019 and 25.346 km^2 in 2021 while NSMI > 0.6 was found occupying 2.168 km^2 in the monsoon period of 2020 compared to 0.010 km^2 and 5.566 km^2 in the very same period of 2019 and 2021 (Table S2). Moreover, the mean NSMI got reduced from 0.494 in the monsoon period of 2019 to 0.437 in the monsoon period of 2020 and during the monsoon period of 2021, it was 0.45 which is lower in comparison to 2019. Significantly, water bodies in the northern and north-western parts of the study area, around the boundary shared with Rajarhat and Salt Lake townships, respectively, have registered a decreasing level of NSMI (Fig. 4).

Considering chlorophyll-α, a significant change was observed in the concentration of chlorophyll-α in 2020 compared to 2019 and 2021. The areal concentration of chlorophyll-α under the range of 1.6 to 2.0 was 5.044 km^2 in 2020 compared to 1.158 km^2 during the monsoon period of 2019. The areal concentration under chlorophyll-α's range of 2.6 to 3 during the monsoon period has decreased in 2020 and 2021 to 5.27 and 5.41 km^2, respectively, from their respective pre-monsoon periods. The mean concentration of Chl-α in the monsoon periods of 2019, 2020, and 2021 were 2.164, 2.012, and 2.043, respectively. A significant intra-year change was also observed in 2020 between monsoon and post-monsoon duration, where a gradual removal of COVID-19 lockdown restrictions might have helped in surging a greater algae concentration compared to the same duration in 2019 and 2021. Areal concentration under the range of 2.1 to 2.5 had decreased by 17% between the monsoon and post-monsoon period in 2020 compared to 36.23% in 2019. While for the range of 2.6 to 3.0 between the monsoon and post-monsoon duration in 2020, it experienced an areal gain of 103.58% compared to a loss of 86.20% in the same duration of 2019. The mean concentration of Chl-α in the post-monsoon period of 2019 and 2020 was 2.086 and 2.129, respectively. Moreover, after the onset of the COVID-19 lockdown in early 2020, the overall algae density was found getting reduced in the study area except in the post-monsoon period of 2020 and pre-monsoon period of 2021 (Fig. 4).

In respect of turbidity, a steady and gradual decrease in the level of turbidity has been observed in 2020 compared to 2019. A turbidity level of less than 1 has portrayed an areal coverage of 4.549 km^2 in the monsoon period of 2020 compared to a clear absence of the same in the monsoon period of 2019 and 2021. Turbidity level ranging from 1.1 to 2.0 has experienced a decrease of 5.88% of the area in the monsoon period of 2020 compared to an increase of 94.62% in 2019 and a decrease of 16.24% in 2021, respectively. While in the case of turbidity range of 2.1 to 3.0, a decrease of 17.79% of the area was observed between the pre-monsoon and monsoon periods of 2020, compared to a decrease of 28.49% of the area in 2019 and an increase of 147.11% in 2021. In the case of a turbidity range from 3.1 to 4 and > 4 between pre-monsoon and monsoon periods of 2020, an increase of 0.855 km^2 (17.05%) and 0.643 km^2 (84.82%) respectively were observed in comparison to 1.758 km^2 (27.89%) and − 0.723 km^2 (− 67.31%) in 2019, respectively. The changes in the very same ranges were found at − 6.295 km^2 (43.37%) and + 1.08 km^2 (56.66%) respectively in 2021 between the pre-monsoon and monsoon periods (Table S2). The mean turbidity level of the lake water during the monsoon periods has varied from 2.237 in 2019 to 1.881 in 2020 and to 2.14 in 2021. Within certain pockets in the northern corner of the study area, the maximum concentration of lowest turbidity was observed, while during the post-monsoon period of 2020, maximum degradation in terms of higher turbidity was evident mostly in the south-eastern pockets of wetlands (Fig. 4).

Regarding SPM, a significant change in the areal concentration under different categories was observed between the pre-monsoon and monsoon periods of 2020 and 2021 compared to 2019. After the COVID-19 lockdown was imposed in the early half of 2020, the levels of SPM in lake water were found to decrease. In the case of SPM ranging from 4.1 to 6, an increase of 2.895 km^2 (32.90%) compared to a decrease of 99.19% in 2019 and a nearly unchanged

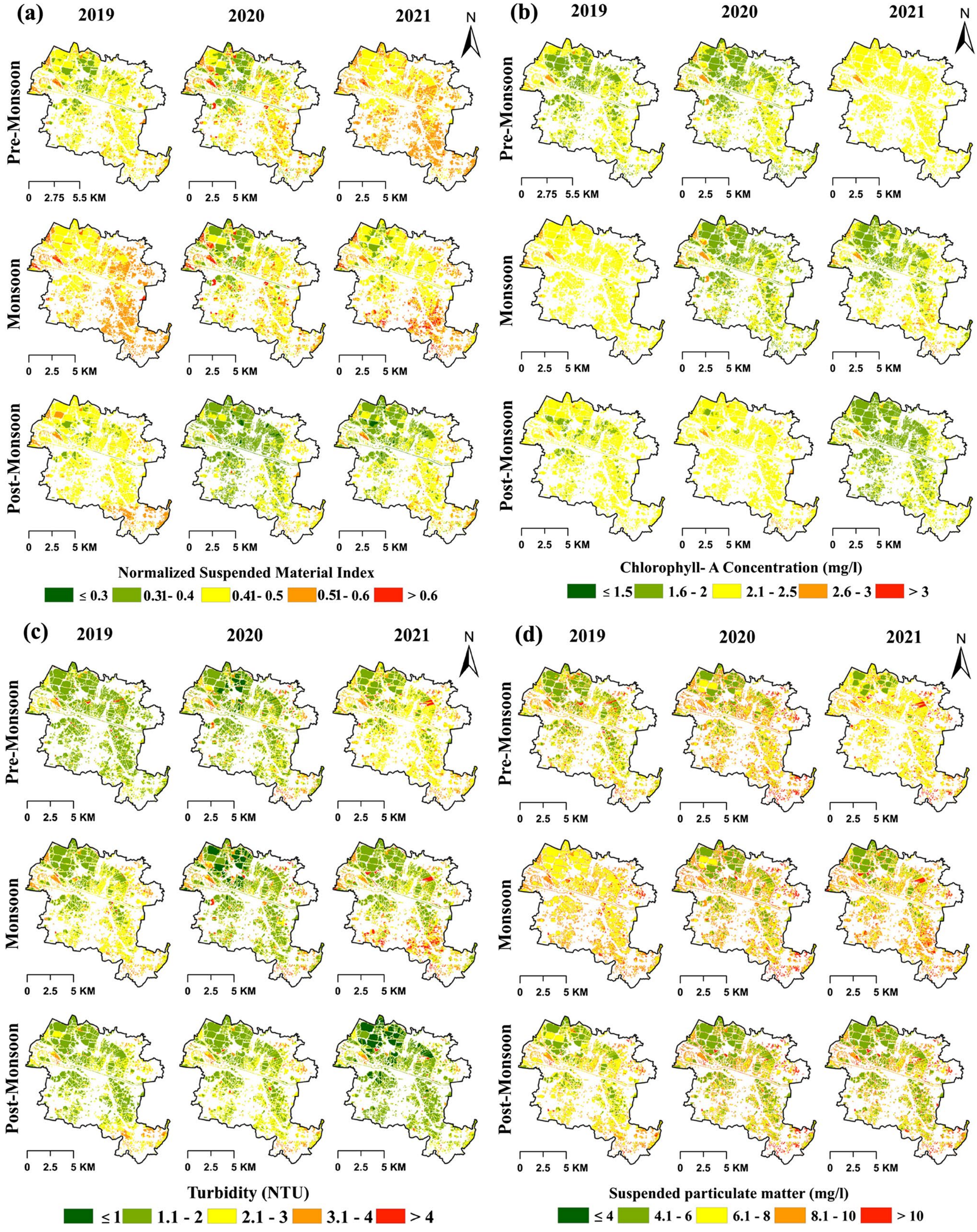


Fig. 4 Improvement of lake water quality **a** NSMI, **b** chlorophyll-α, **c** turbidity, **d** SPM

scenario in 2021. On the contrary to that, the SPM range of 6.1–8 has registered a decrease of 2.862 km^2 (15.60%) in comparison to a decrease of 14.199 km^2 (70.59%) in 2019 and an increase of 9.196 km^2 (122.23%) in 2021. In the case of classes bearing comparatively larger ranges of SPM were also seen depicting signals that the lake water SPM level had overall decreased. In the case of SPM ranges of 8.1–10 and > 10, a decrease of 0.748 km^2 (5.96%) and an increase of 0.717 km^2 (11.02%) respectively were found between the pre-monsoon and monsoon periods of 2020, while for the same duration in 2019, those concerned ranges of SPM had experienced an increase of 23.557 km^2 (282.42%) and 5.553 km^2 (198.96%), respectively. The concentration of SPM was found to have mostly decreased along the transport arteries, mainly in the monsoon period of 2020 due to a lack of vehicle mobility amid the COVID-19 lockdown and partial containment period in 2020 (Fig. 4).

Regarding the total phosphate, a significant inter-season change has been observed in 2020, between pre-monsoon and monsoon seasons compared to the same in 2019. Classes bearing comparatively lower values of total phosphate concentration (≤ 0.5 and 0.6–1.0) have changed their areal occupancy by + 1.179 km^2 (6.04%) and – 0.259 km^2 (12.60%) respectively between the pre-monsoon and monsoon period in 2020, while the same class ranges have registered a change of – 0.847 km^2 (3.56%) and – 12.582 km^2 (63.21%) respectively between the pre-monsoon and monsoon periods in 2019. The mean concentration of total phosphates in the monsoon period of 2020 was measured lower compared to that in 2019 (0.602 and 0.678, respectively). Interestingly, the highest measured range of TP (> 2) was seen to increase between the pre-monsoon and monsoon period of 2020 by 146% (0.11 km^2) compared to a decrease of 62.60% (0.072 km^2) between pre-monsoon and monsoon period of 2019. It was possibly due to certain source point effects as found in Fig. 5 where the emergence of certain waterbodies in the central-northern part of the EKW region during the monsoon period of 2020 had registered a spike in TP value compared to that of 2019. An almost similar pattern of lake water improvement was observed in 2021 between pre-monsoon and monsoon seasons where the classes bearing lower ranges of TP have increased their areal occupancy and the classes bearing higher ranges of TP have decreased.

Regarding electrical conductivity, it is observed that amid the COVID-19 lockdown in 2020, interestingly, an improvement in the EC of EKW water bodies was observed compared to 2019 and 2021. For the EC of ≤ 300 and 301–600, between the pre-monsoon and monsoon 2020, a change of – 15.411 km^2 (74.25%) and 9.773 km^2 (56.81%) was measured respectively with a mean of 360.667 and a maximum concentration of 1322.898. While the same duration in 2019 has recorded a change of – 11.611 km^2 (– 60.14%) and 32.78 km^2 (581%) respectively with a mean of 275.89 and a maximum concentration was 827.967. On the other hand, for the same duration in 2021, it was – 6.822 km^2 (26.65%) and 2.416 km^2 (13.50%) respectively with a mean of 440.27 and a maximum concentration was 1098.15. Classes with greater ranges of EC (601–900, 901–1200, and > 1200) were found to register a negative change in terms of their corresponding areal occupancy between pre-monsoon and monsoon in 2019 and 2021, while the same classes registered positive growth in areal occupancy during the same time interval in 2020.

In respect of the Secchi disk depth, Table S2 elaborates on the multi-temporal nature of the areal occupancy of different classes of SDD. It clearly indicates a scenario with a lower degree of changes in the lake water visibility amid the COVID-19 lockdown in 2020. Classes with comparatively lower ranges of SDD (3.6–4.5 and 4.6–5.5) were found to register a relatively lower degree of changes between the pre-monsoon and monsoon seasons compared to observations found during the very same period in 2019. The changes were 0.105 km^2 (81.39%) and 2.207 km^2 (39.48%) respectively in 2020, while in 2019, the changes were – 0.019 (61.29%) and – 23.68 km^2 (59.79%), respectively. Similarly, in the case of a higher range of SDD (5.6–6.5), the change in areal occupancy was drastic in 2019 between pre-monsoon and monsoon. It was nearly 362% compared to – 5.73% in 2020 which indicates decreasing the visibility of lake water possibly due to greater algae growth during a less dynamic period of land use practices.

Moreover, a clearly distinct and almost opposite trend in SDD was found in 2021 between the pre-monsoon and monsoon periods as compared to 2020. Here, a relative decrease in areal occupancy under comparatively lower ranges of SDD was found to be accompanied by a positive change in the higher SDD range (5.6–6.5), which was mammoth, 645% between the pre-monsoon and monsoon periods. The mean concentration of SDD was measured at 5.35, 5.45, and 5.56 in the monsoon period of 2019, 2020, and 2021 respectively whereas the maximum SDD during the monsoon period was found at 6.051, 6.52, and 6.30 in the respective years. Thus, certain source point influences have controlled the SDD at certain locations amid the lockdown period but the overall changes point towards decreasing the visibility of lake water in the monsoon period of 2020 compared to the same duration in 2019 and 2021 (Fig. 5).

Furthermore, a significant improvement of the FAI in the monsoon period of 2020 compared to that of 2019 has been observed in this study. Since the higher ranges of the FAI denote a greater concentration of algae, larger areal occupancy under lower ranges implies a significant improvement in algae concentration in the lake water. In 2019, between the pre-monsoon and monsoon periods, the change in areal occupancy under FAI ≤ 0.05 was

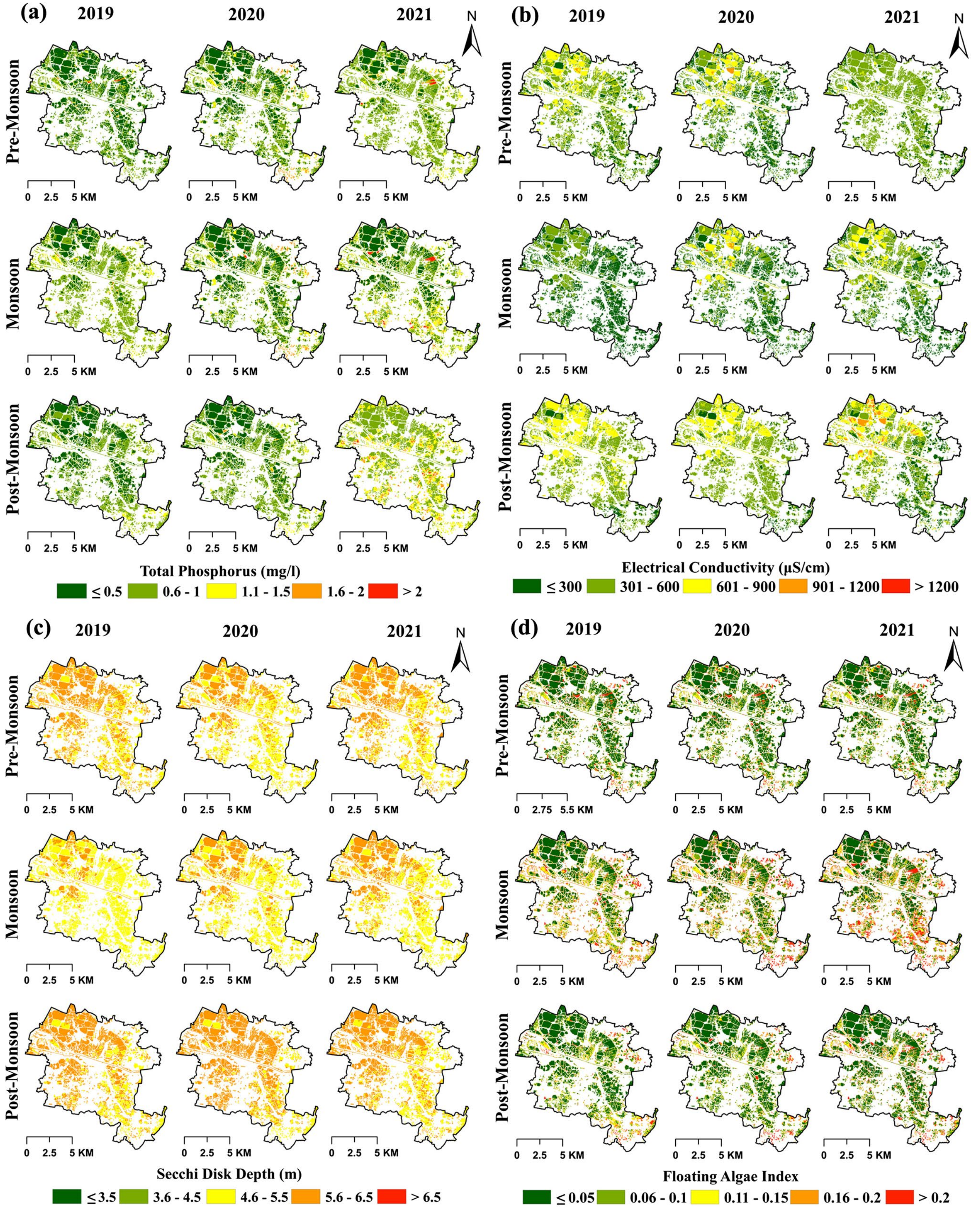


Fig. 5 Improvement of lake water quality **a** total phosphorous, **b** EC, **c** SSD, **d** FAI

323.15% of the area compared to a change of 359.30% in the same duration of 2020. As for other parameters measured between the monsoon and post-monsoon periods, waiving lockdown restrictions in 2020 has played a significant role in the sudden bulging of floating algae in the lake water as the areal occupancy under FAI ≤ 0.05 was found to decrease by 73.3% in comparison to a positive increase in 2019 of 42.25%. The maximum value of FAI measured in 2020 was 0.82 with a mean of 0.0575, 0.894 with a mean of 0.095, and 0.626 with a mean of 0.043 in the pre-monsoon, monsoon, and post-monsoon periods, respectively. It certainly guides towards any potential point sources of an anomaly in the algae concentration due to certain local factors (Fig. 5).

Water quality indices

Lake eutrophication, which results in algae blooms and poor water quality, can be triggered by an excess of nutrients. The TSI represents in situ biological functions in addition to the amount of lake water nutrients. In this study, there was a significant rise in the mean CTSI of the lake water between the pre-monsoon and monsoon periods, from 25.03 to 26.87 in 2019 indicating oligotrophic condition as well as good water quality (Fig. 6). Interestingly, the mean CTSI decreased from 25.38 to 25.31 in 2020 but the highest CTSI score increased from 33.35 to 34.63 between the pre-monsoon and monsoon seasons of 2020 and also indicated oligotrophic condition. Among all the triggering factors (SDD, TP, and Chl-α), a high correlation with TSI was observed for TP indicating that the increased productivity and higher trophic state index of the lake are anticipated to be significantly influenced by TP. The difference between pre-monsoon and monsoon in 2020 for the class range of 0–20 was 206.88%; however, in the monsoon season of 2019 and 2021, no pixel was discovered within this range. Also, from the pre-monsoon to the monsoon period in 2021, the mean CTSI was seen to decline from 26.85 to 26.08, while the rise in areal occupancy by the CTSI range of 31–40 was 81.50% as opposed to a decline of 26.38% between the same periods in 2020.

Finally, the entropy-weighted water quality index integrates the lake water quality parameters: NSMI, Chl-α, Turbidity, SPM, TP, and EC providing a compound status of lake water quality in the EKW region. The maximum compound value of water quality was measured as 92, 82, and 24 in the pre-monsoon, monsoon, and post-monsoon periods of 2019, respectively. Similarly, the maximum EWQI in the pre-monsoon, monsoon, and post-monsoon periods of

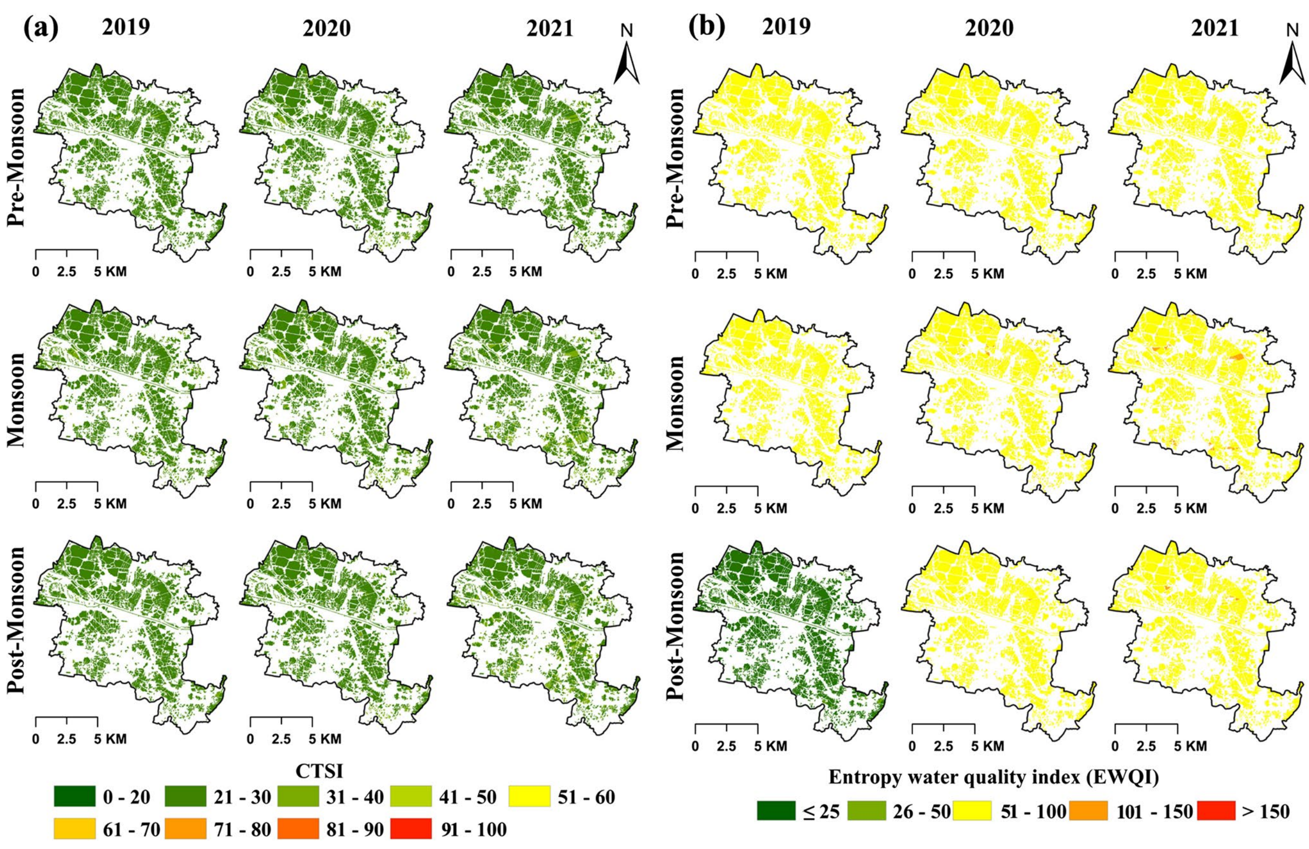


Fig. 6 Improvement of lake water quality **a** CTSI, **b** EWQI

2020 was measured as 83, 69, and 65, respectively. In 2021, these figures were 80, 82, and 87 during the pre-monsoon, monsoon, and post-monsoon periods, respectively. During the monsoon period of 2019 and 2020, the maximum concentration of the lake water was found within the EWQI range of 50–100. Here, the lowest EWQI was measured as 69, 55, and 10 during the pre-monsoon, monsoon, and post-monsoon periods of 2019, respectively. While in 2020, the lowest EWQI was 52, 51, and 57 during the pre-monsoon, monsoon, and post-monsoon periods, respectively. The lowest value of EWQI suggests the improvement of lake water quality status (Mahammad et al. 2022). Although the water bodies were all found concentrating in the range of 50–100 during all the concerned periods of all the years except in the post-monsoon period of 2019, the lowest measured EWQI suggests a relative improvement of lake water quality due to the COVID-19 lockdown condition in 2020 (Fig. 6).

Simulation of EQWI

The prediction of the lake water quality has been done based on a temporal change observed in the target year, the EQWI of the monsoon period of 2020. The simulation was performed considering if the lockdown of the same nature as that administrated in 2020 continued for another 3 years, this prediction of EWQI would be relevant in understanding the water quality status in the monsoon period of 2023. A considerable degree of improvement in the lake's water quality has been predicted in the monsoon period of 2023. The mean EWQI gets reduced from 41.55 to 36.75 and the maximum concentration of the value gets reduced from 89.98 to 47.74 in 2023. Even the minimum value also gets reduced to 25.74 in the predicted raster from 32.10 in the target raster. The gradual betterment has also been seen through the relative areal occupancy under different ranges of EWQI (Table S4 & Table S5). In the case of the target raster (monsoon period of 2020), 88% of the lake surface area is found to be concentrated under the EWQI range of 51–100 and the rest is found lying within the range of 101–150. While in the predicted raster, 84.04% of the total lake surface area is observed to lie within the EWQI range of 26–50 and the rest comes within the range of 51–100 (Fig. 7). The LM algorithm tries to minimize the deviation within the predicted space and helps in getting a minimum spatial error on a non-linear data space.

Validation of the ANN model

The efficiency of the ANN model has been validated using the correlation between the output of the network and corresponding targets. The statistical results demonstrate the effectiveness of ANN and the high (95%) correlations of all relationships (Fig. 8). Higher values of R^2 demonstrate a strong fit between the ANN projected values and the actual measured data. Image-derived water quality metrics were employed in this study to develop EWQI for different phases of lockdown in different seasons and to anticipate the future trend, while field data was used to validate the findings based on the image-based findings.

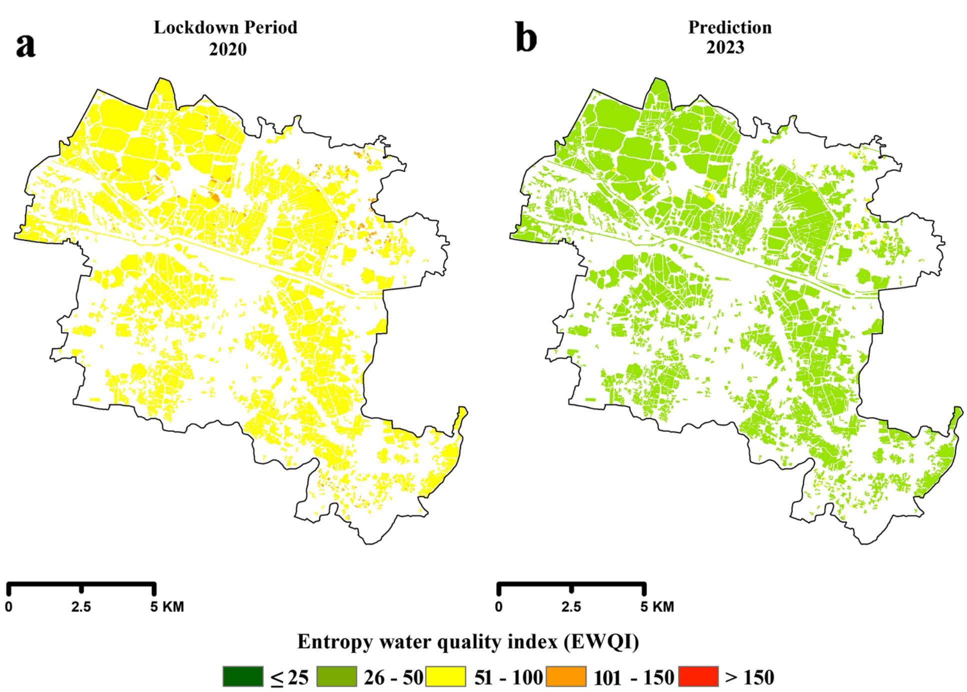


Fig. 7 **a** Prediction of the EWQI using ANN, **b** the prediction is done for 2023 (3-year progression from the lockdown year 2020)

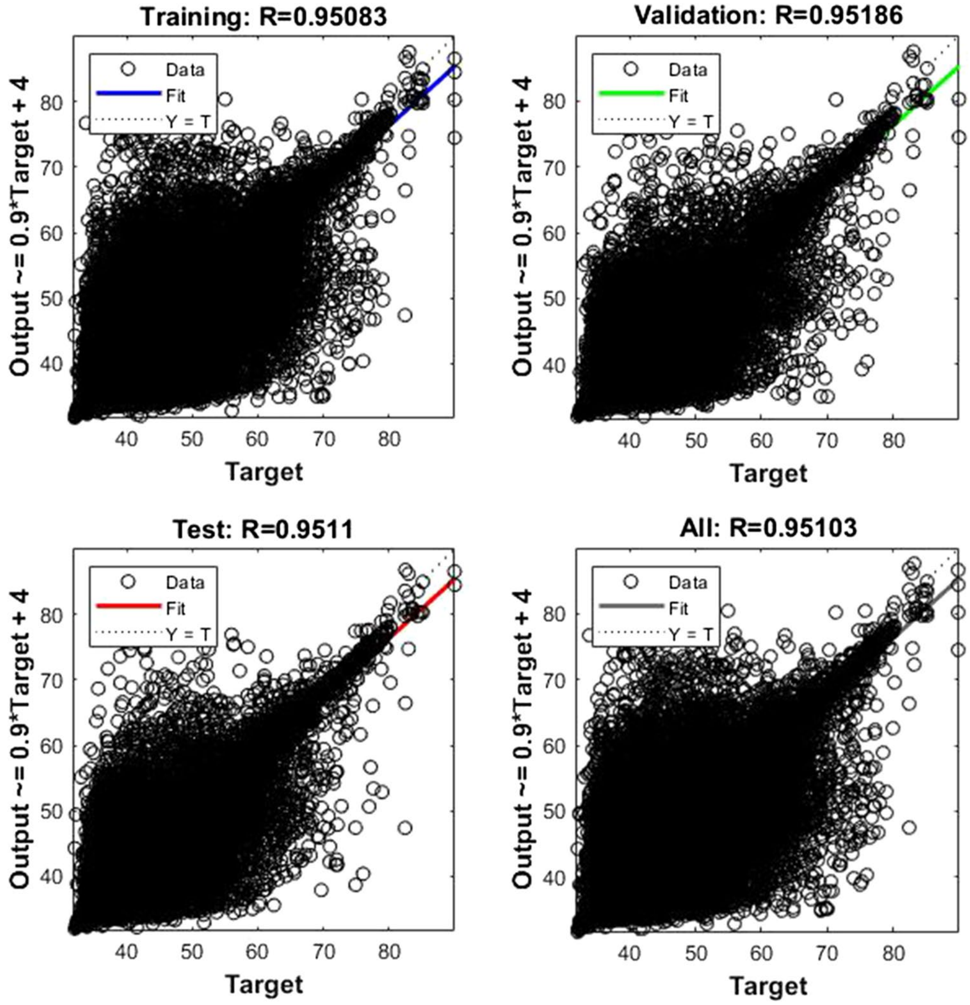


Fig. 8 Performance evaluation of the ANN model

Figure 9 exhibits the relationship between geospatial data and on-site field measurements. The results showed that all the values of correlation coefficient (*R*) are statistically significant at 0.005 level except for TP (post-monsoon) which is significant at 0.05 level.

Relative association between parameters and indices

The relative association of the parameters among each other along with the concerned indices during the considered periods of 2019, 2020, and 2021 has been analyzed (Fig S1 a-i). The correlation between EC and SDD is 1 throughout all other seasons, except for the post-monsoon period of 2019. A significant positive connection between SPM and turbidity was seen across all periods while the relationship between turbidity and TP was also found to be strongly positive, suggesting that turbid water had greater levels of phosphate and SPM concentrations. Contrastingly, turbidity was found negatively correlated with SDD because increasing turbidity reduces the cleanliness of lake water. NSMI was positively correlated with green pigment concentration and turbidity of the lake water. Apart from the association among the different parameters, the association between parameters and indices was also found to be highly significant. All instances showed a close to + 1 correlation between FAI and SPM. Besides, FAI was found to be negatively correlated with SDD (Fig. S1 a-i). It suggests that more than any suspended solids the contribution of algae growth in the lake water was the largest in reducing the lake water's cleanliness and quality. Since algae growth decreases the visibility of lake water, SDD also decreases. Thus, in each of the instances, the FAI was negatively correlated with SDD. Because higher turbidity and suspended particle concentrations reduce lake visibility, these parameters were observed positively correlated with CTSI.

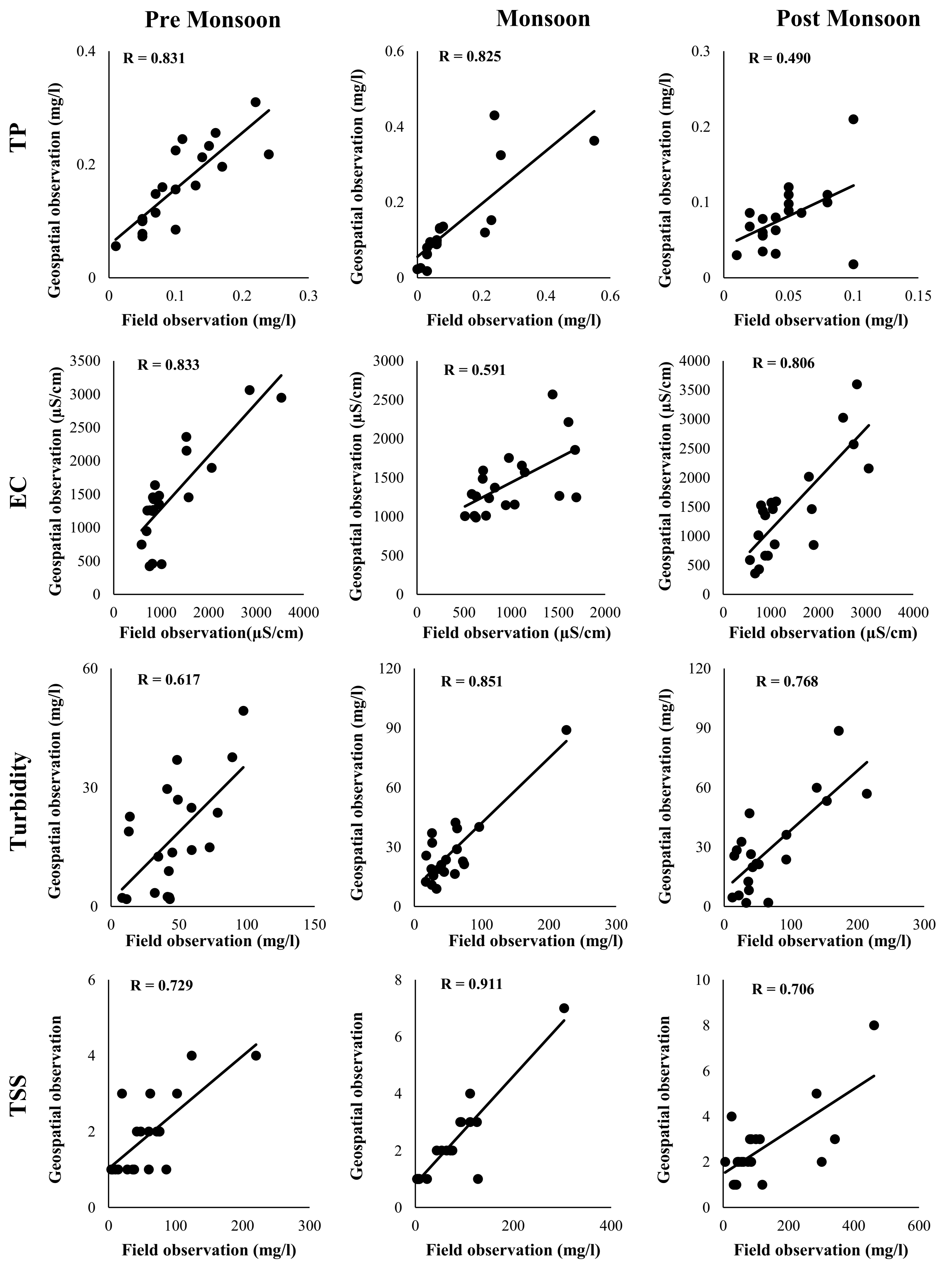


Fig. 9 Relationship between geospatial data and on-site field measurements

Discussion

The nationwide lockdown implemented in India to combat the spread of COVID-19 may have improved the water quality of the EKW region but might not be possible to improve all quality parameters due to having effects on domestic as well as agricultural waste and increased use of medical alcohol and disinfection drugs. The present investigation on EKW confirms that all major parameters of water quality were improved during lockdown periods except for chlorophyll-α and NSMI. Results also indicate that the highest concentration of SPM was recorded during the monsoon of 2019 and the pre-monsoon period of 2021. However, the lake area impacted by high SPM was greater in 2019 than in 2021. In addition, the area under the influence of turbidity was found to be higher in 2019, indicating a higher turbid value. This study also observes that the turbidity index for water followed a definite range for the entire year 2020. Our findings are in line with the study of Yunus et al. (2020). Even though pollution from sources other than industries (like sewage from homes, medicals drugs, and alcohol) continued during the lockdown, our results showed that pollution from industries and medical sectors had a big effect on the quality of the water in the EKW. The maximum EC was found in the 2019 post-monsoon, while the lowest EC was found in the 2020 pre-monsoon. During the lockdown seasons of 2020 and 2021, the conductivity of the lakes was lower than in 2019. Previous studies (Hermans et al. 2014; Sudarshan et al. 2019; Zhu et al. 2016) revealed that temperature and rainfall both have a significant effect on EC. These studies claim that while a rise in rainfall decreases the value of EC, a rise in temperature increases the conductivity of electrolytic conductors, which results in higher levels of EC. Again, from the findings of Sengupta et al. (2021), a drop in temperature and a rise in rainfall of the local climate were seen in many parts of the study zones. Therefore, it is likely that these two meteorological factors had a substantial impact on EC over time, especially during the lockdown. The range of SDD was seen to be the minimum prior to the lockdown period. The monsoons were seen to have the same SDD throughout the entire study period, with the areal extent maximum in 2021 and then in 2020. The SDD value is largely affected by turbidity and SPM, according to earlier studies (Bai et al. 2020; Zeng et al. 2020). Therefore, it can be said that the exemption of various industries and commercial establishments might be the reason why the EKW water quality was seen to be improved. The NSMI results revealed that the highest concentration of suspended material was observed in the post-monsoon period of 2020, whereas the lowest concentration was found in the pre-monsoon 2020. The concentration was increased during the lockdown period than in the pre- and post-lockdown period. The studies of Tokatlı and Varol (2021) found that due to the lockdown, the domestic wastewater or gray water pressure increased and the suspended materials rose throughout the lockdown time. Similarly, due to the presence of a nearby huge urban population and agricultural operations (Fig. 1), our study observed no substantial improvement in suspended material in the EKW region throughout the lockdown period. Phosphorus is widely regarded as the primary limiting factor for lake phytoplankton growth, chlorophyll concentration, and FAI (Jin et al. 2020). Their inter-relationship in this study is utilized to determine the lake trophic state. From the results, a direct relationship between TP and FAI was observed. However, there was an exception in the case of chlorophyll-α concentration measurement in the study region. The elevated concentration of chlorophyll-α during the lockdown phase indicates that the flushing of nutrients from the surrounding agricultural fields and built-up areas to the EKW area which is a pool of stagnant water greatly increased because, during the lockdown period (2020), there was a higher rainfall which accelerated the run-off containing the nutrients (Sengupta et al. 2021).

In terms of overall water quality, we computed two water quality indices, i.e., EWQI and CTSI. The EWQI shows the water quality based on combined essential parameters, while CTSI is computed based on biological and physical parameters. The seasonal EWQI demonstrated that except for the post-monsoon season of 2019, approximately 80% of the wetland was diagnosed as having medium water quality (Kumar and Augustine 2021) in 2020, 2021, and 2019. The post-monsoon season of 2019 was found to have excellent water quality, which accounted for nearly 85% of the wetlands. On the contrary, Carlson's trophic state index (CTSI) is a well-tested, robust statistical technique that incorporates biological and physical elements into consideration. The CTSI result of this study manifests a significant change in water quality, especially in the lockdown period of 2020. A spatial occupancy of CTSI within the range of 0–20 was observed in the pre-lockdown period which increased by 13% in the lockdown period. In this regard, studies by El-Serehy et al. (2018) state that a CTSI value less than 40 suggests that the water body is oligotrophic (low productivity), whereas a value between 40 and 50 denotes mesotrophic (moderate productivity); values greater than 50 signify eutrophic (high productivity) (high productivity). On the contrary, stagnant water and high productivity are anticipated over the lockdown duration. Therefore, with a minimum possibility of anthropogenic factors, climatic variables can be the only plausible cause of this issue.

Conclusions

The lake water quality of the EKW region was examined in this study to understand the anthropogenic and industrial influence during the COVID-19 lockdown (2020) in comparison to 2019 and 2021. According to a metadata study of lake water quality parameters and various indexing methods, most of the parameters decreased throughout the lockdown period as compared to 2019 and 2021. The entire cessation of industrial and anthropogenic activities greatly aided in improving water quality by preventing the mixing of waste effluents immediately dumped into the lake water. Thus, the major findings of the present investigations are mentioned below.

- The COVID-19 lockdown period had a substantial influence on the EKW surface water quality, with considerable reductions in SPM, TP, EC, and turbidity concentrations.
- In terms of overall quality, CTSI and EWQI demonstrated a considerable improvement in water quality at all sites over the lockdown period.
- The short-term simulations using the ANN model also suggest that a significant improvement is anticipated with higher accuracy (~95%) if COVID-19 prevails for the next 3 years. Moreover, the prediction of water quality indicated a great chance to analyze the influence of industrial effluents on surface water quality, and our findings may be utilized to develop water management policies.
- Landsat 8 and 9 data proved effective in measuring different water quality parameters like chlorophyll-α (Chl-α), suspended particulate matter (TSS), and turbidity. High-resolution satellite technologies can play an essential role in the monitoring of the physicochemical qualities of the water of different water bodies.
- It also showed that we can keep natural water resources safe and use them for a long time and that if we manage pollution sources well, we can stop surface water from getting contaminated quickly. In this case, a proper management framework and scientific remediation should be highly useful in restoring lake water quality while allowing human growth to continue in this new normal era. Regular lake health monitoring will significantly minimize anthropogenic stress while also restoring lake resilience, water quality, structure, and biological functions.

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Author contribution Sk Mohinuddin: data curation, formal analysis, investigation, methodology, software, writing—original draft; Soumita Sengupta, Biplab Sarkar, and Ujwal Deep Saha: methodology, writing—original draft; Aznarul Islam: conceptualization, formal analysis, investigation, methodology, writing—original draft, supervision; Abu Reza Md Towfiqul Islam, Wanchang Zhang, and Zakir Md Hossain: original draft preparation, reviewing and editing; Sadik Mahammad, Taushik Ahamed, Raju Mondal, Aimun Basra: data curation, methodology, software, writing—original draft.

Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

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