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Assessment of Water Quality of Khari River in Agra District During Lockdown Period using Multivariant Techniques and Quality Indexes

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Throughout the world, the lock-down period during COVID-19 (March 2020- July 2021) has reported an improvement in the ecological scenario with controlled anthropogenic activities. This study presents a comparative assessment of water quality of the highly polluted Khari river in Agra district (India) during the pre-pandemic and post-pandemic period of COVID-19. The result was analyzed in terms of water quality index (WQI), the most accessed tool used by various researchers to report the water quality. In addition, Aggressive index (AI) and Langelier saturation index (LSI) have also been determined. Further, multivariate analysis has been performed in terms of principal component analysis (PCA). ANOVA has been used to study the variance of the parameters. The study revealed a positive impact of pandemic on the water quality as the parameters improved during the post-pandemic period as compared to the pre-pandemic period. However, as the river was highly polluted during the pre-pandemic period, strict actions are required for further improvement in its water quality for agricultural, industrial and industrial use.

Keywords: Water quality index, Aggressive index, Langelier saturation index, Principal component analysis, ANOVA.

INTRODUCTION

During the pandemic time of COVID-19, the pandemic (imposed in March 2020) restricted various anthropogenic activities across the world, one of the prime causes of pollution [1]. Over the pandemic time, the decline of industrial waste production, industrial emissions and the introduction of heavy metals and plastic to the hydrosphere have all significantly decreased. As a result, a decline in environmental pollution is expected by the researchers and needs to be quantified [2]. The urbanization and industrialization due to ever increasing human population along with tremendous agricultural practices, has resulted in accumulation of waste that end up in the nearby water sources causing a wide impact on water quality [3,4]. In many parts of earth, the geographical, climatic and hydrological changes also alter the quality of the groundwater [4-6]. Furthermore, heavy metals, which are common trace components of the marine system, as well as most toxic compounds that may be deposited in the biota, are usually discharged into the water bodies from factories, agricultural fields and municipal water run-offs, thus creating contamination [7-10].

Dimri *et al.* [11] reported during the analysis of river Ganga that the most common water pollutants include pesticides, herbicides, fertilizers, liquid and solid wastes from sewage plants, septic tanks, slaughter houses and other pollutants especially heavy metals such as mercury, lead, chromium, copper and cadmium that has a major effect on the physico-chemical composition of water and the ecology of hydrological system. Dissolved minerals beyond the allowable limit as set by BIS are deemed non-desirable for usage. Pandit *et al*. [12] reported that high amounts of dissolved minerals are harmful to animals and plants and it is not suitable for irrigation purposes. When the contaminated water seeps into the soil and enters an aquifer, it also results into ground water contamination. Njugana *et al*. [13] emphasized that water quality of any water source must, in all cases, be controlled both before its use and during its use.

Khari river in Agra city stretches from Kheragarh to Fatehpur Sikri and is actually a perennial and effluent type of river that has been severely affected by the industrial effluents. Increasing urbanization and industrialization at Agra are adding to the emission capacity of the river Khari. The village and town communities situated upstream of the river have evidently gotten into the habit of disposing wastewater and hazardous waste in a messy fashion and as a result have created a lot of contamination. The contamination of the river Khari has reached such a degree that it has made the water absolutely undrinkable and is jeopardizing the survival of flora and fauna in the river. When the water level decreases during the season, there is less water in the main stream, which creates a large rise in contamination leading to emanation of foul odor from the water. river bank cremation is a common procedure leading to disposal of half burnt bodies in the river leading to decomposition. It seems that the once large and fast-flowing river Khari will run dry in the immediate future and be replaced by a stagnant creek bearing disease-ridden streams. Farmers who rely on irrigation from the contaminated water have to endure devastating crop yields and lower-quality crops. It is, therefore, desirable to monitor the pollution level and study the physical, chemical and biological characteristics and to investigate the causative factors responsible for causing pollution in Khari river.

This study is focused on the water quality assessment of Khari river in terms of comparative investigation of various parameters of different location samples during the pre-pandemic (April 2019 to January 2020) and post-pandemic period (June 2020 to February 2021). The results have been expressed in terms of water indexes including Aggressive index (AI), Langelier Saturation Index (LSI) and water quality index (WQI). Multivariant techniques have been used to analyze the effect of pandemic on water quality and a comparative assessment has been explored.

Historical background of Agra district: Agra is an administrative unit of Uttar Pradesh, the state of northern India [14]. It is a historic and industrial city that is supplied with vast network of river Yamuna and its tributaries [14,15]. The city has an area of 1884 km^2 and a population of 4,380,793 (2011 census). Agra is bounded by Aligarh district of Uttar Pradesh state to the north and the Uttar Pradesh districts of Mathura the West, Dholpur to the South, Bharatpur to the south west, Firozabad to the East [15]. Khari river links to Utangan river, one of the tributaries of river Yamuna that controls the drainage of Agra city flowing 20 km to its west. It is a spring fed drainage line of Uttar Pradesh, originates near village Chiksana (Chauma) of district Agra. Extending between the coordinates of 27º11′N to 27º18′N and 78º01′E to 78º02′E approximately, it drains an area of about 120 km^2. It mainly drains the parts belonging to Shamsabad and Kiraoli Tehsils. It takes water from a number of small streams and a major portion is diverted into a canal for irrigation purposes. During its downward flow it passes through Kiraoli, Akola and ultimately it merges in the river Utangan in Agra city.

EXPERIMENTAL

All the chemicals used for the study were procured from Sigma-Aldrich and used as such. All the formulations were prepared using deionized water.

Sampling sites: To evaluate the impact of contaminants on Khari river, water samples were collected over the stretch of 40 km. from Village Chiksana (Chauma) to town Iradat Nagar, Samsabad road, Agra as listed in Table-1, by collecting and analyzing the water samples from different places in the pre-pandemic and post-pandemic period. The study area belonging to Khari river has been shown in Fig. 1.

TABLE-1
LOCATION OF SAMPLE STATIONS OF KHARI RIVER

Sample station	Location of river
I	After village Chiksana, Chauma
II	After town Kiraoli-Kagarole Marg bridge
III	After Akola Jagner Road bridge
IV	After railway bridge Agra-Gwalior B.G. Line (N.C.R.)
V	After Iradat Nagar

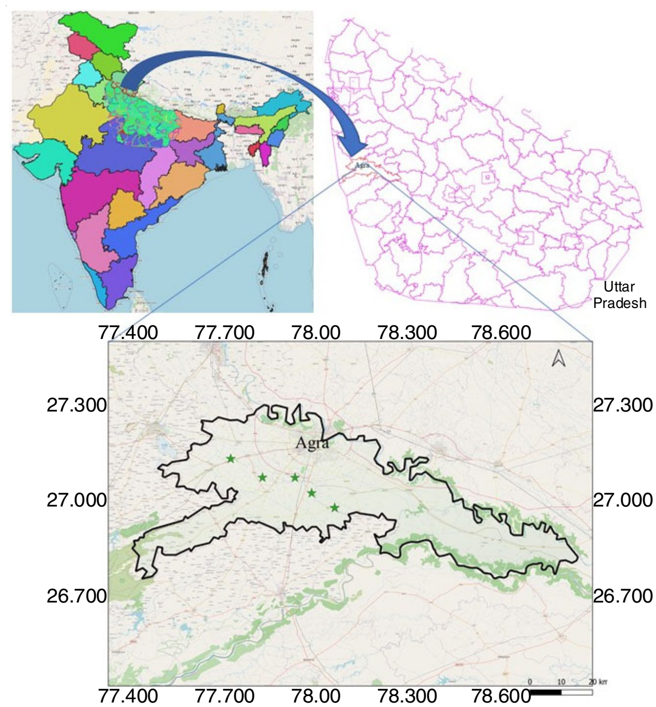

Fig. 1. Geological map of area under study

Collection of samples: Composite samples from multiple sampling sites in five different areas were used to analyze their physical properties. The samples were drawn from five different sites and then combined to get a composite sample. To ensure that the water was free of air bubbles, the bottles were rinsed three times with the water. The samples were kept in a temperature controlled refrigerator at 4 ºC.

Quantitative analysis: The determination of various physicochemical parameters including pH, conductivity, total dissolved solids (TDS), total alkalinity (TA), total water hardness (TWH), calcium hardness (CH), magnesium hardness (MH) along with anions including carbonate (CO_3^{2-}), bicarbonate (HCO_3^-), chloride (Cl^-), nitrate (NO_3^-) and sulphate (SO_4^{2-}) was carried out as per standard procedures [12].

Index analysis: Aggressive index (AI) [16], Langelier saturation index (LSI) [16] and water quality index (WQI) [12] was determined after the quantitative analysis and the range has been listed in Table-2.

TABLE-2
SUMMARIZED INFORMATION OF INDEXES USED IN THE STUDY

Name of index	Range	Water quality
Aggressive index (AI)	< 10	Very aggressive
	10-11.9	Moderately aggressive
	> 12	Non-aggressive
Langelier saturation index (LSI)	< 0	Unsaturated water with respect to calcium carbonate
	0	Neutral
	> 0	Supersaturated water with respect to calcium carbonate
Water quality index (WQI)	< 50	Excellent
	50-99.99	Good
	100-199.99	Poor
	200-299.99	Very poor
	> 300	Unsuitable for use

AI and LSI were computed to determine corrosiveness of water samples using eqns. 1 and 2, respectively:

$$AI = pH + \log (TA \times CH) \quad (1)$$

$$LSI = pH - pH_s \quad (2)$$

where pH_s is the saturation pH.

Simple arithmetic mean and aggregated technique was used to measure the WQI, where water quality characteristics (Q_i) are multiplied by a weighting factor (W_i) and the resulting measurements are aggregated as per eqn. 3:

$$WQI = \frac{\Sigma Q_i W_i}{\Sigma W_i} \quad (3)$$

where W_i was obtained from the permissible standard value (S_i) of the parameters using eqn. 4:

$$W_i = \frac{1/\Sigma(1/S_i)}{S_i} \quad (4)$$

Statistical analysis: XLSTAT was used for the statistical analysis of the parameters under study. The ANOVA test has been used for comparing the variances to understand the effect of time period on the data set (p value > 0.05). Pearson correlation coefficient (p value > 0.05) has been evaluated in order to determine the correlation between the water quality parameters [11]. Further Box-whiskers were explored for all the data set. For three season datasets of pre-monsoon, monsoon and post-monsoon, ANOVA and coefficient of correlation are applied independently. In addition, independent principal component analysis (PCA) was performed on two distinct groups comprising of five distinct locations. PCA returns eigen values greater than 1 and eigenvectors, a list of loadings and produces a covariance matrix. Kaiser-Meyer-Olkin (KMO) and Bartlett sphericity techniques have been used for monitoring the effectiveness of PCA prior to implementation of PCA on the dataset [9].

RESULTS AND DISCUSSION

The presence of excessive mineral and toxic compounds in water not only lead to dangerous impacts on human health but is also unadvisable for industrial and agricultural use [17,18]. In addition, corrosiveness of water due to presence of certain minerals, may damage water distribution and purification systems. In particular, the use of polluted and contaminated water for irrigational purpose can severely impact the soil quality and crop yield. Hence, the water quality must be evaluated to placate these objectives [19]. The result of the quantitative and physico-chemical analysis has been discussed ahead in detail and the statistics of parameters under study has been summarized in Table-3.

Quantitative analysis: Conductance of a solution is due to the electric current carried by the dissolved ions and hence is a direct measure of the presence of ions in the water sample. Higher the concentration of the ions, higher is the conductance of the sample [6]. The introduction of various ions in water bodies due to effluent discharge from the nearby industrial and various agricultural operations directly affect the conductance of the water. Water with high conductance is not suitable for drinking, irrigational as well as industrial purpose [15]. The conductance of water samples was found to range from 771.54 µS to 1935.29 µS with an overall average value of

TABLE-3
STATISTICS OF PARAMETERS UNDER STUDY

Variable	Pre-pandemic period				Post-pandemic period			
	Minimum	Maximum	Mean	Std. deviation	Minimum	Maximum	Mean	Std. deviation
pH	6.28	6.46	6.37	0.06	6.39	6.75	6.57	0.17
ELC (µS)	1151.73	1487.49	1344.22	124.39	957.34	1541.33	1198.38	265.77
TDS (ppm)	806.21	1041.24	940.96	87.07	670.14	1078.93	838.86	186.04
TA (ppm)	72.83	118.07	88.76	21.60	63.60	84.45	75.41	7.86
TWH (ppm)	174.72	278.22	230.66	39.68	155.70	271.70	204.92	56.37
CH (ppm)	94.56	191.76	139.52	35.35	106.13	167.27	135.28	29.41
MH (ppm)	80.10	106.66	91.13	10.52	48.53	104.64	72.26	25.09
Cl^- (ppm)	80.54	117.92	99.00	14.54	67.73	111.71	85.44	21.38
SO_4^{2-} (ppm)	91.59	113.53	100.87	8.84	73.28	114.27	89.22	18.14
NO_3^- (ppm)	26.46	48.66	35.84	8.56	24.75	48.75	33.87	10.07
AI	10.49	10.82	10.64	0.12	10.49	10.82	10.64	0.12
WQI	133.08	164.67	148.98	13.99	133.08	164.67	148.98	13.99
LSI	-1.45	-1.14	-1.32	0.13	-1.45	-1.14	-1.32	0.13

1344.22 µS during the pre-pandemic period. However, after the pandemic period, the range varied from 699.22 µS to 1656.099 µS with overall average value of 1325.27 µS.

TDS quantifies the dissolved ions along with organic matter in water. Estimation of TDS in water is very important before its use for domestic, industrial and agricultural processes [1]. In general, river water has a higher TDS due to its enrichment by salts from its origin and trajectory over the rocks in addition to contamination from industrial effluents and agricultural as well as domestic runoffs [3]. TDS of water samples was found to vary from 540.08 to 1354.70 ppm averaging at 940.96 ppm in the pre-pandemic period. Comparatively, lower TDS was observed in post-pandemic period with values in between 489.46 to 1159.26 ppm with 927.69 ppm as an average value. As per BIS guidelines, the samples from some places were found as almost brackish with TDS >1000 ppm [20]. Fig. 2 shows the variation of conductance and TDS during the time period of study.

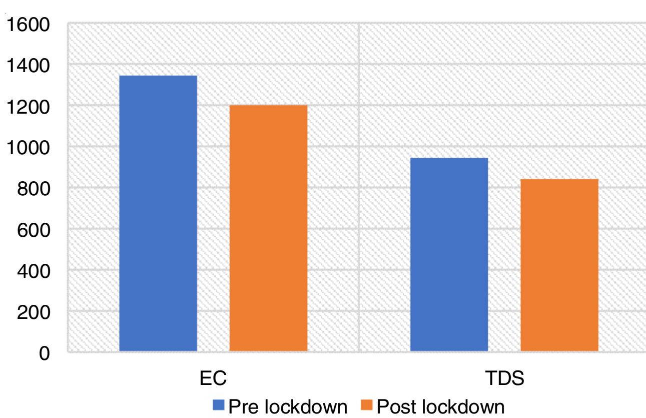

Fig. 2. Variation of conductance and TDS during the study

Total alkalinity (TA) of water measures the number of dissolved carbonates and bicarbonates in water with its permissible value ranging as 200-600 ppm [14]. Total alkalinity of water samples varied in the range of 43.93-158.46 ppm with an average value of 88.76 ppm in the pre-pandemic period indicating the high susceptibility of water samples for pH change. In the post-pandemic period, the value ranged from 42.00 to 113.15 ppm resulting in an average of 88.96 ppm. During the pre-pandemic period, the value of carbonate alkalinity was detected to vary from 24.52-66.80 ppm with an average value as 47.46 ppm. The carbonate alkalinity was found to increase slightly with value ranging in between 27.59-70.25 ppm with an increase in average value as 57.56 ppm. Bicarbonate alkalinity ranged from 15.69-93.21 ppm and an overall average of 41.30 ppm in analyzed samples during pre-pandemic period. A slight decrease in value of bicarbonate alkalinity was observed during the post-pandemic period with a minimum value of 14.41 ppm to a maximum value of 42.89 ppm with an average of 31.40 ppm. Total water hardness (TWH) of water measures the number of cations and anions such as carbonates, bicarbonates and anions including sulphate, nitrate and chloride, *etc.* which may render water unsuitable for domestic, industrial and agricultural use [20]. TWH of water samples ranged from 105.78 to 376.80 ppm with overall average of 230.66 ppm for water analysis during pre-lock down period. The value was found to decrease during the post-pandemic period with a minimum value observed as 93.00 ppm and a maximum value of 304.20 with an average value as 224.48 ppm.

The most common hardness in any water sample is due to calcium and magnesium [21]. The calcium hardness of water samples ranged from 65.64-277.80 ppm with overall average of 139.52 ppm during pre-pandemic period. The value ranged from 82.80-238.80 ppm during the post-pandemic period with an average value of 139.08 ppm. During the pre-pandemic period, the magnesium hardness ranged from 40.14-158.40 ppm with overall average of 91.13 ppm. However, during the post-pandemic period a comparatively lower average value of 85.79 ppm was observed with a value range of 24.60-131.40 ppm. Fig. 3 shows the variation of various physico-chemical parameters during the time period of study.

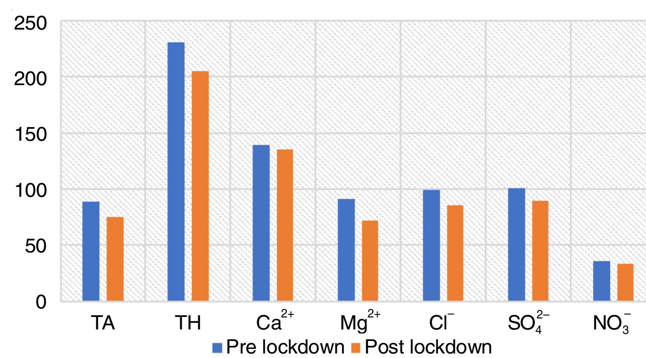

Fig. 3. Variation of physico-chemical parameters during study

During the pre-pandemic period, sodium values ranged from 66.00 to161.50 ppm and the average value was 118.14 ppm. The maximum value of sodium examined in post- pandemic period was 74.40 ppm and the minimum value of sodium measured was 160.65 with an average value as 134.12 ppm. On the other hand, potassium values ranged from 0.94 to 11.40 ppm in the pre-pandemic period with an average value as 4.67 ppm. The maximum value of potassium examined in post-pandemic period was 11.76 with a minimum value as 1.56 ppm. The average value was detected as 4.84 ppm.

In natural water bodies, the greatest contributor to chloride ions is the disposal of sewage discharge. As per BIS standards, the permissible limit of chloride in water bodies is less than 250 ppm [13]. Overall, the chloride concentration in water ranges from 60.57 to 186.0 ppm and an average value of 99.00 ppm was reported during the pre-pandemic time. An average value of 87.83 ppm was reported during the post-pandemic time with range varying as 59.40-141.00 ppm with an average value.

The sulphate ion is normally present in all kinds of water and an effective hardness-contributing ion. Many anthropogenic and biogeochemical sources could be responsible for the higher sulphate concentration [21]. The sulphate ion concentration in water samples ranged from 67.50 to 165.60 ppm during the pre-pandemic period with an overall average of 100.87 ppm. On the other hand, the range decreased to 59.40-126.60

ppm during the post-pandemic period with an average of 93.90 ppm. The most common water-contaminant sources of nitrate pollution are industrial effluents, sewage discharge and run-offs from agricultural and urban processes leading to eutrophication [13]. A higher nitrate level (> 45 ppm) in drinking water causes methemoglobinemia in children. Nitrate concentrations in the analyzed samples ranged from 17.85 ppm to 64.50 ppm during the pre-pandemic time with an average value as 35.84 ppm. During the post-landing time, the average value increased to 33.86 ppm with a range varying in between 16.20-70.50 ppm.

Corrosive index: pH is an important parameter that indicates the acidic (pH < 7) or alkaline (pH > 7) nature of water and is directly affected by presence of various minerals and pollutants. The acceptable limit of pH as per BIS ranges from 6.5-8.5 [20]. The pH of the analyzed samples was found to vary from 6.04 to 6.80 during the pre-pandemic period (average value as 6.37) and from 6.04 to 6.97 during the post-pandemic period (average value as 6.67). A significant and positive change was observed in the areas where major activities were restricted. During the pre-pandemic analysis, out of 40 samples, 29 samples were found to have higher pH than the permissible limit, while the number declined to 16 during the post-pandemic samples. In order to determine corrosion potential of water samples of study area, two corrosivity Indices namely Aggressive index (AI) and Langelier saturation index (LSI) have been calculated. The calculated values of Aggressive index (AI) for all the samples analyzed in pre-pandemic period ranged from 9.98 to 11.21 with an overall average of 10.64. While in the post-pandemic period, the values varied from 10.05 to 11.24 and the average value was 10.73 as represented in Fig. 4. Data reveals that maximum samples show moderator aggressive to aggressive nature of corrosivity [16]. On the other hand, LSI was observed to -1.93 to -0.61 with an overall average of -1.32 during the pre-pandemic period. The values were found to improve with mean value as -1.18 during the post-pandemic period with range in between -1.89 to -0.65 (Fig. 5). Data reveals that nature of water samples of study area were neither severe corrosive nor severe scale/encrustation but usually mild conditioning is required [16].

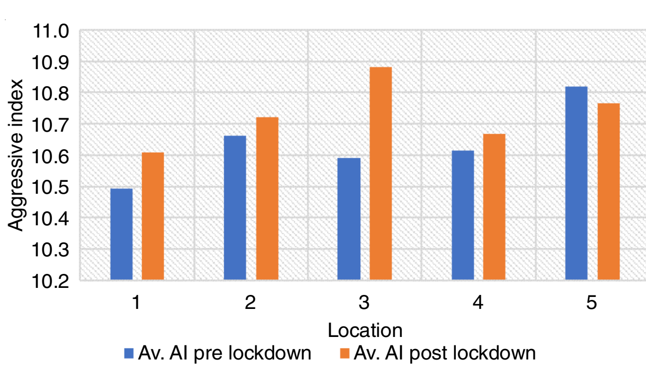

Fig. 4. Variation of AI during the study

Water quality Index (WQI): WQI of the samples was found to vary from 87.16 to 188.08 during the pre-pandemic period with an average value as 148.98 and from 59.17 to 190.88 during the post-pandemic period with an average value

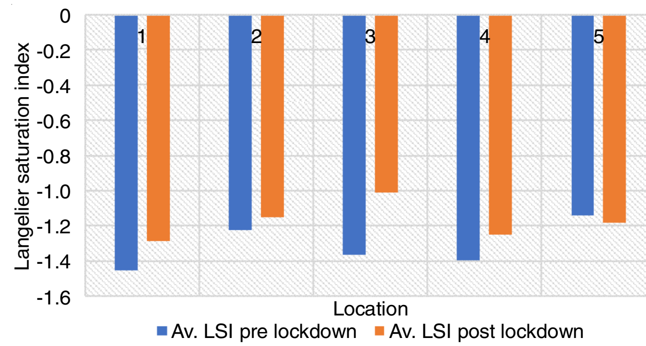

Fig. 5. Variation of Langelier saturation index (LSI) during the study

as 113.41. The analysis indicated the water of Khari river as highly polluted and unfit for use in agricultural, industrial as well as domestic purposes [12]. Out of the five sample sites, I was found to have the lowest WQI and IV was found to exhibit the highest WQI indicating the latter as the most polluted area among the five (Fig. 6).

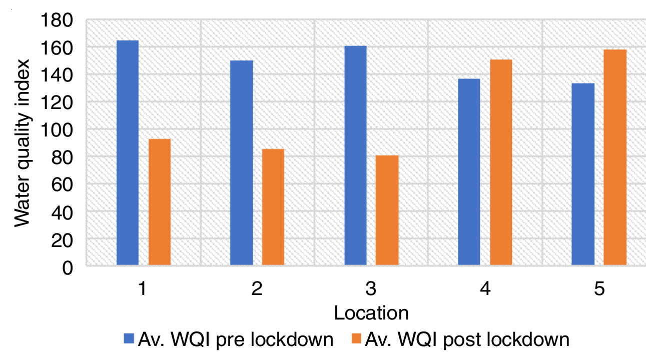

Fig. 6. Variation of WQI during the study

Seasonal effect of water quality was mostly observed for all parameters considered under the study. Results revealed that TDS values were higher in post-monsoon season as compared to pre-monsoon due to leaching of various salts into water. In most of the areas, nitrate concentration was found to increase in the post monsoon period. However, an overall analysis of water samples collected for these study areas indicate the presence of higher TA, TWH and TDS during the pre-pandemic period that was found to improve during the post-pandemic period due to limited anthropogenic activities. Even then, the study of water quality parameters revealed that the water at area was still found to be highly polluted [12]. Hence, due monitoring and strict actions are required to improve the water quality of Khari river. Since, water quality is most affected by agricultural runoff, industrial drainage, thermal power stations and urban sewage, these pollutants in the water could continue to decrease in partial lockdown of the human activities in the affected areas [22].

Statistical analysis: During ANOVA analysis, all parameters had very significant results ($p < 0.0001$) as listed in Table-4. KMO and Bartlett's test for the parameters reported adequacy of sampling as listed in Table-5 indicated significant correlation. Tables 6 and 7 shows the Pearson correlation matrix and the positive values of Pearson correlation coefficients for

TABLE-4
GOODNESS OF FIT STATISTICS AND ANALYSIS OF VARIANCE FOR PARAMETERS UNDER STUDY

	Pre-pandemic period	Post-pandemic period
DF	36	36
R^2	0.987	0.954
Adjusted R^2	0.982	0.940
RMSE	54.524	95.825
PC	0.022	0.077
F	239.909	67.944
Pr > F	<0.0001	<0.0001

TABLE-5
KMO AND BARTLETT'S SPHERICITY TEST

	Pre-pandemic period	Post-pandemic period
KMO measure of sampling adequacy	0.557	0.666
Bartlett's sphericity test		
Chi-square (critical value)	99.617	99.617
Alpha	0.050	0.050

all the parameters under study can be observed from Tables 8 and 9 for pre-pandemic and post-pandemic period, respectively.

TABLE-6
PEARSON CORRELATION MATRIX FOR PARAMETERS UNDER STUDY IN PRE-PANDEMIC PERIOD

Variables	pH	ELC	TDS	TA	TWH	CH	MH	Cl^-	SO_4^{2-}	NO_3^-	AI	WQI	LSI
pH	1												
ELC	-0.044	1											
TDS	-0.044	1.000	1										
TA	0.768	-0.627	-0.627	1									
TWH	-0.264	0.969	0.969	-0.795	1								
CH	-0.137	0.948	0.948	-0.698	0.967	1							
MH	-0.531	0.473	0.473	-0.649	0.523	0.289	1						
Cl^-	0.021	0.962	0.962	-0.620	0.942	0.936	0.409	1					
SO_4^{2-}	-0.058	0.912	0.912	-0.682	0.930	0.941	0.347	0.982	1				
NO_3^-	-0.794	0.424	0.424	-0.731	0.534	0.386	0.715	0.240	0.210	1			
AI	0.985	0.074	0.074	0.717	-0.159	-0.041	-0.457	0.102	0.000	-0.680	1		
WQI	-0.873	0.478	0.478	-0.915	0.634	0.469	0.812	0.392	0.410	0.914	-0.800	1	
LSI	0.891	0.378	0.378	0.463	0.162	0.293	-0.369	0.390	0.293	-0.506	0.941	-0.614	1

TABLE-7
PEARSON CORRELATION MATRIX FOR PARAMETERS UNDER STUDY IN POST-PANDEMIC PERIOD

Variables	pH	ELC	TDS	TA	TWH	CH	MH	Cl^-	SO_4^{2-}	NO_3^-	AI	WQI	LSI
pH	1												
ELC	-0.904	1											
TDS	-0.904	1.000	1										
TA	-0.454	0.778	0.778	1									
TWH	-0.928	0.995	0.995	0.736	1								
CH	-0.919	0.986	0.986	0.748	0.994	1							
MH	-0.950	0.973	0.973	0.627	0.976	0.950	1						
Cl^-	-0.938	0.995	0.995	0.714	0.998	0.987	0.987	1					
SO_4^{2-}	-0.916	0.991	0.991	0.722	0.983	0.960	0.991	0.991	1				
NO_3^-	-0.861	0.985	0.985	0.811	0.965	0.947	0.954	0.969	0.985	1			
AI	-0.543	0.724	0.724	0.815	0.672	0.672	0.623	0.669	0.708	0.811	1		
WQI	0.889	-0.911	-0.911	-0.707	-0.916	-0.937	-0.857	-0.906	-0.878	-0.897	-0.800	1	
LSI	-0.297	0.454	0.454	0.643	0.393	0.399	0.346	0.390	0.440	0.571	0.941	-0.614	1

TABLE-8
PEARSON CORRELATION COEFFICIENTS FOR PARAMETERS UNDER STUDY IN PRE-PANDEMIC PERIOD

Variables	pH	ELC	TDS	TA	TWH	CH	MH	Cl^-	SO_4^{2-}	NO_3^-	AI	WQI	LSI
pH	1												
ELC	0.002	1											
TDS	0.002	1.000	1										
TA	0.589	0.394	0.394	1									
TWH	0.070	0.939	0.939	0.631	1								
CH	0.019	0.898	0.898	0.488	0.935	1							
MH	0.282	0.224	0.224	0.421	0.273	0.083	1						
Cl^-	0.000	0.926	0.926	0.384	0.888	0.877	0.167	1					
SO_4^{2-}	0.003	0.832	0.832	0.465	0.865	0.885	0.120	0.964	1				
NO_3^-	0.631	0.180	0.180	0.535	0.285	0.149	0.512	0.058	0.044	1			
AI	0.971	0.005	0.005	0.513	0.025	0.002	0.209	0.010	0.000	0.462	1		
WQI	0.762	0.228	0.228	0.837	0.402	0.220	0.660	0.153	0.168	0.835	0.640	1	
LSI	0.794	0.143	0.143	0.214	0.026	0.086	0.136	0.152	0.086	0.256	0.886	0.377	1

TABLE-9
PEARSON CORRELATION COEFFICIENTS FOR PARAMETERS UNDER STUDY IN POST-PANDEMIC PERIOD

Variables	pH	ELC	TDS	TA	TWH	CH	MH	Cl^-	SO_4^{2-}	NO_3^-	AI	WQI	LSI
pH	1												
ELC	0.817	1											
TDS	0.817	1.000	1										
TA	0.206	0.606	0.606	1									
TWH	0.862	0.991	0.991	0.542	1								
CH	0.844	0.971	0.971	0.560	0.989	1							
MH	0.903	0.947	0.947	0.393	0.952	0.902	1						
Cl^-	0.879	0.990	0.990	0.509	0.996	0.974	0.974	1					
SO_4^{2-}	0.839	0.981	0.981	0.521	0.967	0.921	0.982	0.982	1				
NO_3^-	0.740	0.970	0.970	0.658	0.932	0.897	0.910	0.939	0.971	1			
AI	0.295	0.524	0.524	0.664	0.452	0.452	0.389	0.447	0.501	0.658	1		
WQI	0.791	0.830	0.830	0.500	0.839	0.877	0.734	0.820	0.771	0.805	0.640	1	
LSI	0.088	0.206	0.206	0.413	0.155	0.159	0.120	0.152	0.194	0.326	0.886	0.377	1

Significant correlation was obtained between TDS and TWH, TWH and EC, TWH and Ca^{2+} as well as EC and Cl^- indicating a strong interdependence of these parameters.

The Box-Whisker plots for all the water quality parameters during the pre-pandemic and post-pandemic periods have been illustrated in Figs. 7 and 8, respectively. Larger the box, greater is the variation in the dataset of the particular property. Within the catchment region, the lower and upper whiskers display the lowest and highest observed values accordingly [11]. It can be observed that at different sampling locations, different water quality parameters show different levels of variation. Major fluctuations within the mean values of Ca^{2+} and WQI were found in the pre-pandemic period. More variance was seen in the values of SO_4^{2-} during the post-pandemic period.

During the PCA analysis, the cumulative proportion is used to evaluate the variance explained by the principal components within the acceptable level of variance and with the eigen values having value > 1 [9]. Table-10 shows the eigen values and vectors obtained after PCA. The three primary components (PCs) have their own corresponding eigen values, which are all higher than one [23]. It can be seen that 92.06% and 95.62% of the variance in the data respectively for the pre-pandemic and post-pandemic period can be explained by the first two components also illustrated from the scree plot as shown in Fig. 9. It can also be observed that in the pre-pandemic period, first principal component has high positive associations with TWH followed by EC, TDS, Ca^{2+}, SO_4^{2-}, Cl^- and WQI while high negative association with TA. On the other hand, high positive association of LSI, AI and pH is obtained with second principal component. Thus, first principal component measures the physico-chemical parameters while the index parameters are measured primarily by the second principal component. However, during the post-pandemic period, except pH and WQI, all the parameters under study have a positive association with the first principal component. From the biplot as illustrated in Fig. 10, it is observed that the corrosive indicators are highly associated forming cluster due to similar gene expression response. Similarly, the physico-chemical parameters form another cluster being highly associated [24].

Conclusion

The lockdown during the COVID-19 pandemic has exposed a new series of worldwide experiments for the researchers to analyze the effect of anthropogenic activities on the ecosystem.

TABLE-10
EIGEN VALUES AND EIGEN VECTORS FOR THE EXTRACTED COMPONENTS

	Pre-pandemic period				Post-pandemic period			
	F1	F2	F3	F4	F1	F2	F3	F4
Eigen value	7.550	4.418	0.678	0.355	10.979	1.452	0.414	0.155
Variability (%)	58.075	33.981	5.216	2.728	84.452	11.173	3.182	1.193
Cumulative %	58.075	92.056	97.272	100.000	84.452	95.625	98.807	100.000
Eigen vectors								
pH	-0.185	0.402	0.182	-0.122	-0.272	0.271	0.446	0.083
ELC	0.319	0.222	0.116	0.120	0.300	-0.080	0.110	0.043
TDS	0.319	0.222	0.116	0.120	0.300	-0.080	0.110	0.043
TA	-0.334	0.155	0.253	0.145	0.239	0.327	0.717	-0.219
TWH	0.349	0.132	-0.052	0.079	0.297	-0.140	0.073	-0.095
CH	0.317	0.197	-0.262	0.243	0.295	-0.125	0.078	-0.360
MH	0.249	-0.163	0.687	-0.513	0.289	-0.204	-0.069	0.367
Cl^-	0.304	0.250	-0.062	-0.251	0.297	-0.152	0.033	0.037
SO_4^{2-}	0.304	0.219	-0.274	-0.327	0.296	-0.106	0.027	0.352
NO_3^-	0.257	-0.254	0.346	0.618	0.299	0.033	0.077	0.310
AI	-0.150	0.418	0.291	0.052	0.239	0.497	-0.146	0.135
WQI	0.301	-0.263	0.131	0.022	-0.285	-0.064	0.307	0.643
LSI	-0.041	0.463	0.179	0.229	0.166	0.666	-0.351	0.119

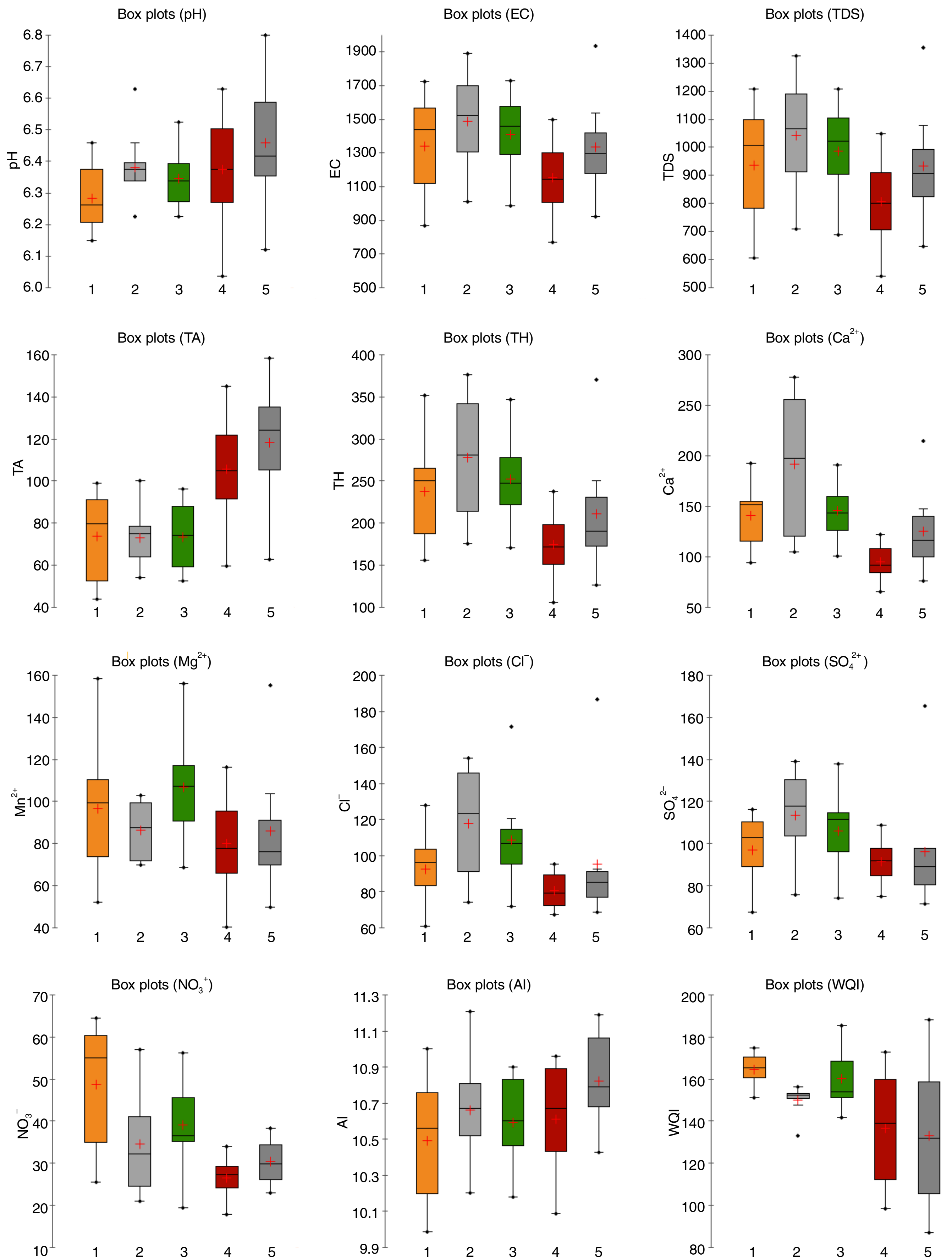

Fig. 7. Box-plot of parameters during study during pre-pandemic period

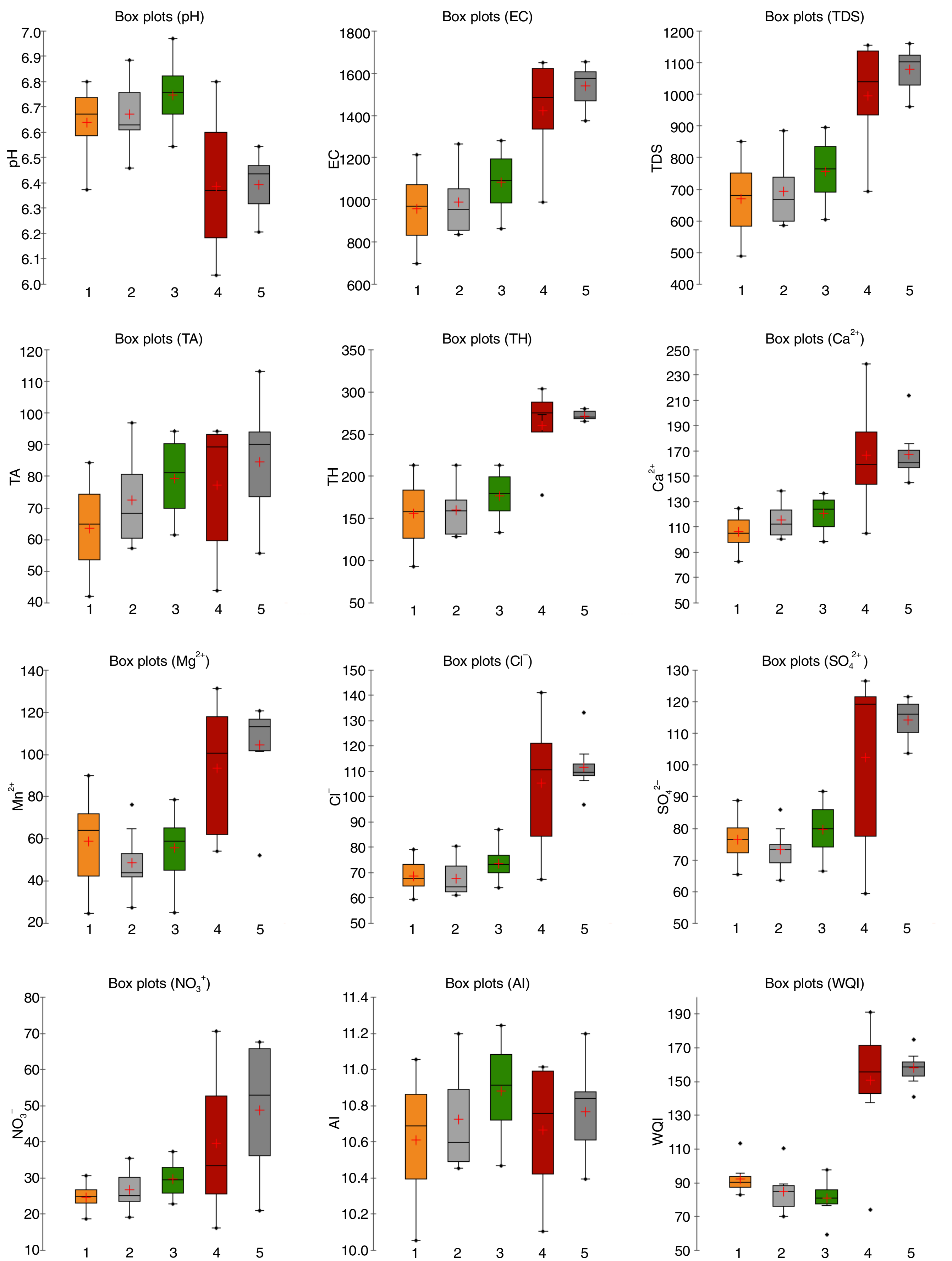

Fig. 8. Box-plot of parameters during study during post-pandemic period

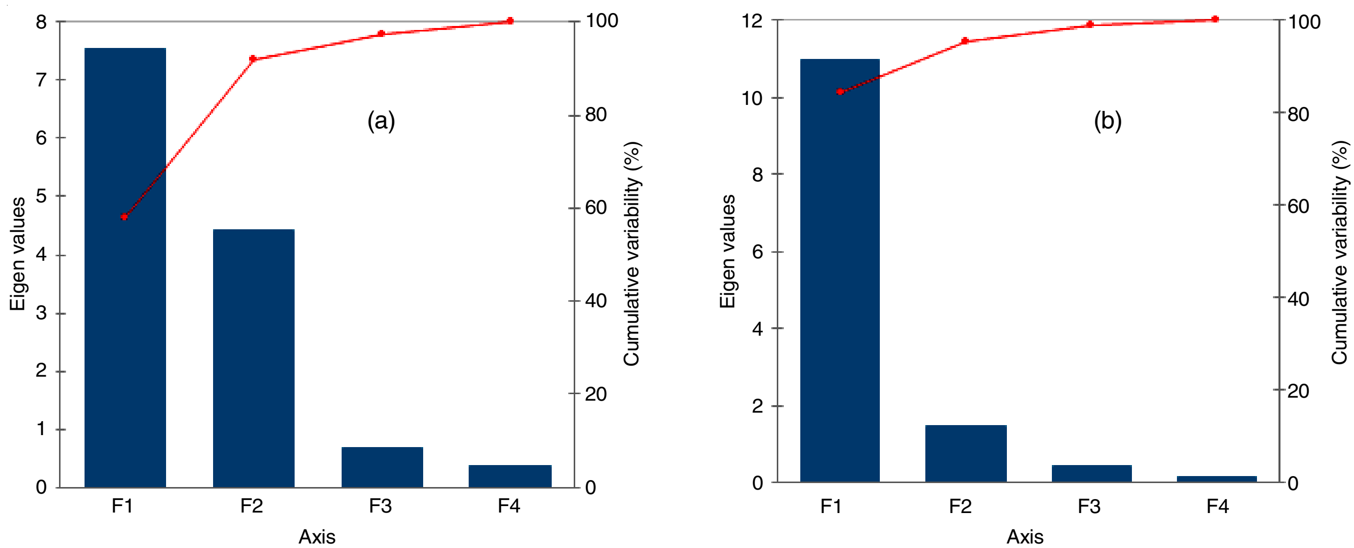

Fig. 9. Scree plots after PCA of the parameter during (a) pre-pandemic period b) post-pandemic period

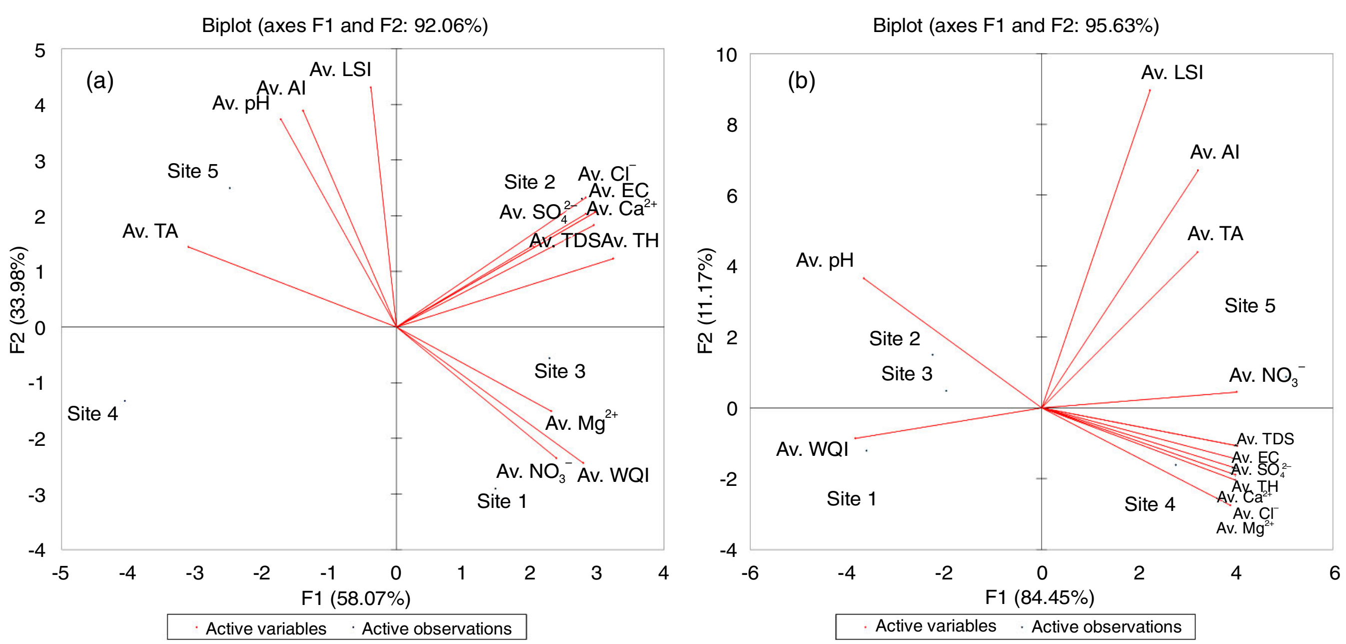

Fig. 10. Biplots after PCA of the parameter during (a) pre-pandemic period (b) post-pandemic period

The present study analyses the water quality of five areas near Khari river at Agra District during the pre-pandemic and post-pandemic period. The study reveals that the river water was highly polluted with high value of total alkalinity (TA), total water hardness (TWH) and total dissolved solids (TDS) during the pre-pandemic period that improved slightly during the post-pandemic period. PCA analysis revealed a strong correlation between these parameters. The water quality index was also found to improve significantly during the post-pandemic period. As a result, it was found that restoration is based on controlling the intervention of anthropogenic activities in the natural processes. Thus, an essential part of the solution to environmental pollution is the implementation of stringent legislation to control anthropogenic practices and discharge of effluents from small as well as large-scale industrial operations.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this article.

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