Journal of Applied and Natural Science
15(1), 379 - 390 (2023)
ISSN : 0974-9411 (Print), 2231-5209 (Online)
journals.ansfoundation.org

Research Article

Evaluation of water quality of Mundeswari River in eastern India: a water quality index (WQI) based approach

Pratyush Ghosh*
Department of Zoology, University of Kalyani, Kalyani, Nadia-741235 (West Bengal), India; Department of Zoology, Chandernagore College, Chandannagar, Hooghly-712136 (West Bengal), India
A.K. Panigrahi
Department of Zoology, University of Kalyani, Kalyani, Nadia-741235, West Bengal, India

*Corresponding author. Email: pratyushghosh60@gmail.com

Article Info
https://doi.org/10.31018/jans.v15i1.4340
Received: December 28, 2022
Revised: March 2, 2023
Accepted: March 7, 2023

How to Cite
Ghosh, P. and Panigrahi, A. K. (2023). Evaluation of water quality of Mundeswari River in eastern India: a water quality index (WQI) based approach. *Journal of Applied and Natural Science*, 15(1), 379 - 390. https://doi.org/10.31018/jans.v15i1.4340

Abstract

The Mundeswari River is the western distributary of the Damodar River system in eastern India. The water of this river is extensively used for domestic purposes and agricultural irrigation. This study aimed to evaluate the spatial and temporal water quality variation of the Mundeswari River and assess the water quality status of this river using the Canadian Council of Ministers of the Environment Water Quality Index (CCME-WQI). Water quality was monitored monthly at four selected sampling stations (M1, M2, M3, and M4) during 2020-2022, considering twelve selected water quality indicators. The obtained water quality data were analysed using different statistical techniques. Water quality at different monitoring stations was appraised through the use of CCME-WQI. The results revealed that the overall water quality of most of the monitoring stations based on CCME-WQI values was "marginal." The highest WQI value (82.01) was observed at M1, and the lowest WQI (41.24) was recorded at M3. One-way ANOVA indicated a statistically significant difference in WQI values between sampling sites ($P < 0.05$). The water quality of the M3 sampling station was found to be in degraded condition throughout the study period. Cluster analysis from the perspective of WQI values revealed two distinct clusters of the sampling stations. Substantial seasonal variation in water quality was also observed. This river had putrid water quality during the pre-monsoon period, and relatively better water quality was evident after the monsoon. This study revealed that the water of the Mundeswari River is utterly unsafe for human consumption and it requires significant treatments before it can be safely used for domestic purposes like cooking, washing etc.

Keywords: CCME, Correlation, Mundeswari River, Water quality, WQI

INTRODUCTION

Rivers as sources of freshwater are crucial to the sustenance and prosperity of civilization. Riverine ecosystems are regarded as the most dynamic ecosystems (Choudhury *et al*., 2022). Rivers provide critical habitats for a wide range of animals, plants, and microorganisms. River water has extensive applications in all economic sectors, especially agriculture, aquaculture, industries, and waterways transport. River ecosystems are also subjected to multiple stressors that affect their structure and functioning (von Schiller *et al*., 2017). Protecting river water quality is one of the most serious global challenges. Degradation of the river water quality can result from both natural processes and, more recently anthropogenic activities. Massive amounts of domestic sewage, agricultural drainage, and industrial effluents enter the rivers, resulting in a dramatic deterioration of water quality. Regular water quality monitoring is necessary to prevent river water quality from deteriorating. River water quality evaluation is also crucial for human health and safety due to its multifaceted usage (Ghosh and Panigrahi, 2018; Bilgin, 2018; Mamun and An, 2021).

It might be challenging to understand and interpret complex "long-term water quality monitoring data" involving many water quality parameters (Yotova *et al*., 2021). Water quality index (WQI) is the most efficient mathematical tool used to assess water quality by converting large complex datasets of many water quality characteristics into straightforward numeric rating scales (Matta *et al*., 2020). WQI converts the raw data of a variety of quality parameters into single-value information and expresses the data in a "simplified and logical form" (Gitau *et al.*, 2016; Semy and Singh, 2021). The role of WQI is very significant for assessing river water quality as it gives a comprehensive interpretation of the river water quality and its appropriateness for various uses, such as drinking, irrigation, etc.(Bora and Goswami, 2017; Chou *et al.*, 2018; Mukate *et al.*, 2019). The concept of WQI was conceived more than a decade after the notion of water quality was developed to classify water of diverse streams and lakes according to the degree of pollution of the watercourse(Abbasi and Abbasi, 2012). A myriad of WQIs have been designed across the world, such as US National Sanitation Foundation Water Quality Index (NSF-WQI), Scottish Research Development Department Water Quality Index (SRDD-WQI), Oregon Water Quality Index (OWQI), British Columbia Water Quality Index (BCWQI), Canadian Council of Ministers of the Environment Water Quality Index (CCME-WQI), etc.(Şener *et al.*, 2017). Because of the increasing relevance and acceptability of new hybrid soft computing techniques like machine learning and artificial intelligence in the field of WQI development, the idea of integrated approaches has emerged in recent years (Najah Ahmed *et al.*, 2019; Verma *et al.*, 2019).

At the dawn of the twenty-first century, the CCME model evolved from the BCWQI Model (Gupta and Gupta, 2021; Lumb *et al.*, 2011). The CCME-WQI model mandates using at least four water quality variables (Uddin *et al.*, 2021). Three statistical indicators—scope, frequency, and amplitude—were mathematically combined to form the CCME-WQI (Terrado *et al.*, 2010).The CCME-WQI model has been used on a variety of surface water resources across the globe. It is used relatively often because it is easy to use and allows users to select which water quality parameters should be included in the model (Abbasi and Abbasi, 2012; Uddin *et al.*, 2021). Munna *et al.* (2013) evaluated the pollution level of the Surma River in Bangladesh from the perspective of the CCME-WQI, considering fourteen water quality parameters. This investigation concluded that the river was considered to be in "poor" condition by CCME-WQI. Hamlat *et al.* (2016) assessed the water quality of Tafna river basin, Algeria utilizing thirteen Water quality parameters and found that CCME-WQI was a very useful and informative tool for figuring out the potability of the river water. Regmi *et al.* (2017) applied the CCME-WQI, considering ten water quality parameters to evaluate the water quality of some major rivers in the Kathmandu Valley, including the Bagmati River. Abdel-Satar *et al.* (2017) appraised the suitability of Nile River water using CCME-WQI. The water quality of the Coruh river basin was investigated using the CCME-WQI by Bilgin (2018). This research demonstrated that CCME-WQI values offered reliable insight into the water quality of the river. Recently, Panagopoulos *et al.* (2022) used CCME-WQI for physico-chemical quality evaluation of Greek rivers and Marselin *et al.* (2022) applied this index to evaluate the water quality of Citarum River in Indonesia. In India, Sharma and Kansal (2011) used the CCME-WQI to measure the water quality in the Yamuna River in India. Haldar *et al.* (2014) investigated the Damodar River (upper stretch) water quality using this water quality index.

Mundeswari River is the western distributary of Damodar River in eastern India. This river is flood prone and its lower segment is tidal in nature. In recent years, this river is greatly impacted by intense land use, the congregation of human settlement, and ongoing developmental activities. The river, through the highly fertile plains of southern Bengal in eastern India, receives pollutants from both the point and non-point sources. This river water is extensively used for domestic purposes and for agricultural irrigation.

A review of the relevant literature finds that no extensive research has been conducted on the water quality and pollution levels of the Mundeswari River. The flood risk assessment of this river has been the subject of only a handful of studies (Sanyal *et al.*, 2014; Singh *et al.*, 2020). Therefore, a detailed assessment of the water quality of the Mundeswari River is essential. The objective of this study was to investigate the spatiotemporal fluctuation of selected water quality parameters and to assess the riverine water quality using the Canadian Council of Ministers of the Environment Water Quality Index (CCME-WQI). The findings of this study could serve as a baseline for adopting future policies and conservation measures to restore the ecological health of this river.

MATERIALS AND METHODS

Study area

The Mundeswari River is one of the significant right-hand distributaries of the mighty Damodar River. After originating from the Damodar River near Jamalpur in West Bengal, India, the Mundeswari River traverses through the Hooghly and Howrah districts of West Bengal before meeting with the Rupnarayan river. The channel system of the Mundeswari river at its lower stretches is anabranching in nature and is characterized by several distributary channels. The lower reaches of this river are impacted by regular tidal inflow from the estuary. This river basin suffers from chronic flooding incidents. This river is located in the tropical monsoon climatic zone. The riverbed is composed of sand and clay. The land use of this river basin is dominated by agriculture (Sanyal *et al.*, 2014). The highly fertile alluvial plains of this river lead to a congregation of human settlements right up to the bank of this river.

Water sampling and physico-chemical analysis

Water samples were collected at monthly intervals between July 2020-June 2022 from four predesignated sampling stations, the minimum distance between two consecutive sampling stations was 10 km. Details of the sampling stations are given in Fig. 1. Sampling strategy was designed to cover a wide array of water quality parameters that represent physical characteristics, aggregate organic constituents, and nutrient content of the water sample. Sub-surface water samples were collected from each sampling site in high-density polythene or glass container. Water temperature, pH, TDS, and conductivity were measured in situ immediately after the collection of water samples. Dissolved oxygen content was similarly fixed with Winkler's reagent on-site. The collection, preservation and conveyance of the collected water samples were accomplished following standard protocols (American Public Health Association (APHA), 2017). Analytical-grade chemicals and reagents were used for the analysis. Different physico-chemical water quality parameters, along with their abbreviations (if used), unit of measurement and methods/techniques used for their analysis, are summarized in Table 1.

Estimation of CCME-WQI

The Canadian Council of Ministers of Environment (CCME) has introduced a universally accepted flexible model by which ambient water quality could be expressed in terms of an index (CCME-WQI) considering several parameters (Haldar *et al.*, 2014; Hassan *et al.*, 2018; Yotova *et al.*, 2021).

The CCME WQI computation is based on three factors that characterise the anthropogenic influences on water quality:

F1(Scope): This represents the percentage of total parameters that do not meet the corresponding regulatory guideline value or specific objective ("failed variables"). It is expressed as:

$$F1 = \left[\frac{Number\ of\ failed\ variables}{Total\ number\ of\ variables}\right] \times 100 \quad \text{Eq. 1}$$

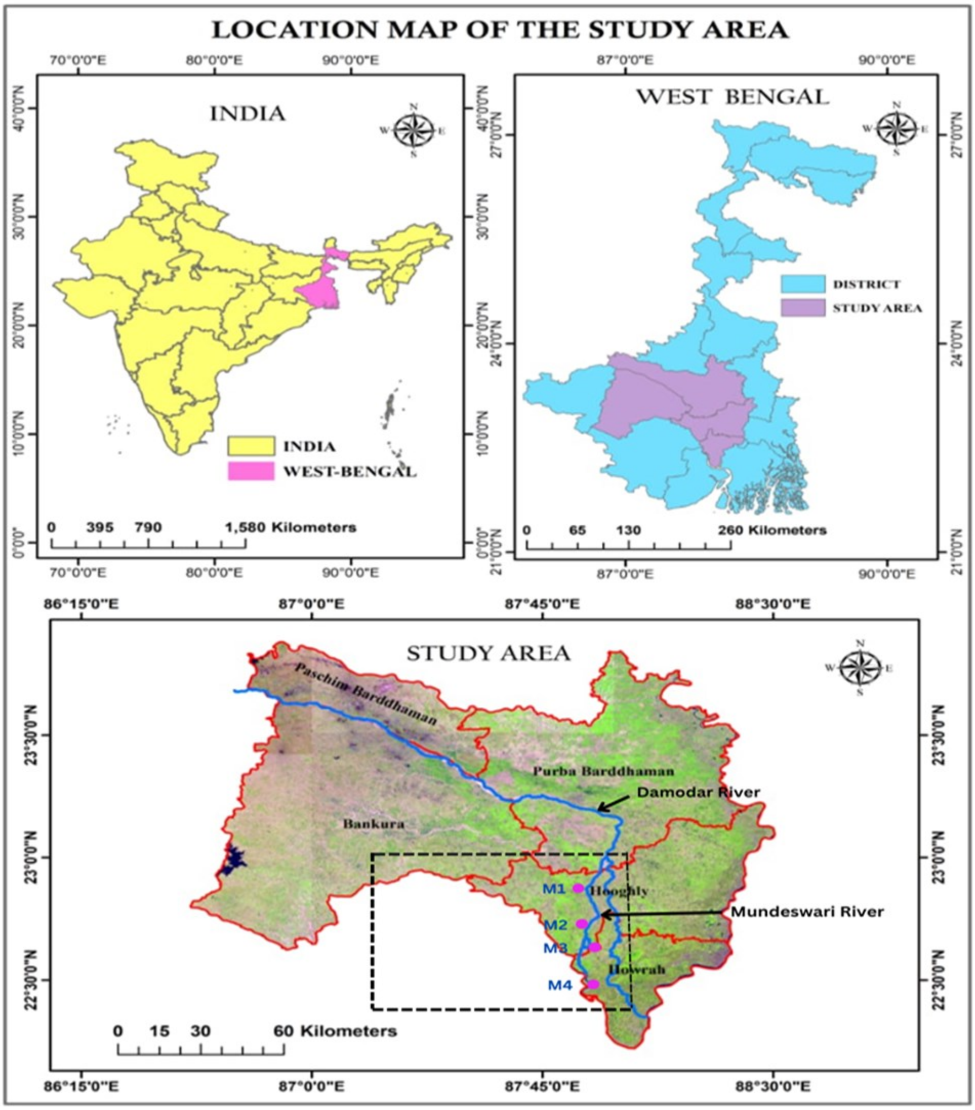

Fig. 1. *Location of the water quality monitoring stations in Mundeswari River*

F2(Frequency): This represents the percentage of individual test values that failed to meet the objectives ("failed tests"). It is numerically expressed as:

$$\mathrm{F2} = \left[\frac{Number\ of\ failed\ tests}{Total\ number\ of\ tests}\right] \times 100 \quad \text{Eq. 2}$$

F3(Amplitude): This represents the extent of deviation of the non-compliant or failed test values relative to the corresponding regulatory guideline values.

It is calculated in three steps.

Step1: ***Calculation of excursion***

If the test value falls below the objective value, the excursion value can be calculated using the following equation

$$\mathrm{excursion_i} = \left[\frac{\text{failed test value}}{objective_j}\right] \times 100 \quad \text{Eq. 3}$$

In case the test value exceeds the objective, the excursion value can be obtained using following equation

$$\mathrm{excursion_i} = \left[\frac{objective_j}{failed\ test\ value}\right] \times 100 \quad \text{Eq. 4}$$

Step 2: ***Calculation of normalized sum of Excursions (nse)***

The nse is the collective amount through which individual test values are out of compliance. It is worked out by dividing the summation of all excursions by the total number of tests. It is mathematically expressed as:

$$\mathrm{nse} = \frac{\sum_{i=1}^{n} excursion}{Total\ number\ of\ tests} \quad \text{Eq. 5}$$

Step 3: ***Calculation of Amplitude***

After calculating the nse, amplitude is then calculated by an asymptotic function that scales the nse from the objective within 0-100.

$$\mathrm{F3} = \left[\left[\frac{nse}{0.01(nse)+0.01}\right]\right] \quad \text{Eq. 6}$$

The final calculation of WQI by aggregation of the obtained factors as follows:

$$\mathrm{CCMEWQI} = 100 - \left(\frac{\sqrt{F1^2+F2^2+F3^2}}{1.732}\right) \quad \text{Eq. 7}$$

The normalisation factor of 1.732 is employed to assure that the resulting WQI is between 0 and 100, with 0 representing the poorest water quality and 100 indicating the superb water quality. Water quality is graded into five categories within this range: "poor," "marginal," "fair," "good," and "excellent" (Table 2).

Statistical analysis

All the analytical data collected at monthly intervals were pooled under three seasons per year, namely pre-monsoon (March-June), Monsson (June-October) and post-monsoon (November to February). The water quality data were statistically processed to assess the descriptive statistical parameters. A Pearson's correlation analysis was performed to determine which water quality parameters had a significant linear relationship. The correlation coefficient (r) value close to +1 and -1 indicates a strong positive and negative correlation between the two parameters (Cho *et al.*, 2022). According to the values of the correlation coefficient, the interrelationship between the two parameters can be defined as follows:0.9-1; very high,0.7-0.89; high,0.5 -0.69; moderate,0.26-0.49; weak,0-0.25; very weak (Ustaoğlu and Tepe, 2019).Hierarchical cluster analysis was applied to discern the similarities among sampling stations based on CCME-WQI score. All the statistical analysis was

Table 1. Water quality variables analysed during 2020-22 in Mundeswari River

Parameter	Abbreviation used	Unit	Analytical method
pH			pH meter
Total dissolved solids	TDS	mg/L	TDS meter
Electrical conductivity	EC	mg/L	Conductivity meter
Total hardness	TH	$CaCO_3$ mg/L	Titrimetric
Total alkalinity	TA	$CaCO_3$ mg/L	Titrimetric
Calcium	Ca	mg/L	Titrimetric
Magnesium	Mg	mg/L	Titrimetric
Turbidity	TUR	NTU	Nephelometric
Biochemical oxygen demand	BOD	mg/L	5-day BOD test
Dissolved oxygen	DO	mg/L	Winkler's iodometric
Nitrate-nitrogen	NO_3-N	mg/L	Spectrophotometric
Sulphate	SO_4	mg/L	Spectrophotometric

Table 2. Categorization of CCME-WQI Values (Haldar *et al.*, 2014; Uddin *et al.*, 2021)

Categories	CCME-WQI Value	Comments
"Excellent"	95-100	The water quality is not threatened; it has not deteriorated & is close to natural levels.
"Good"	80-94	The water quality is somewhat threatened & seldom falls below desired levels.
"Fair"	65-79	The overall water quality is usually protected but occasionally threatened or impaired.
"Marginal"	45-64	Almost poor water quality; The water quality is frequently threatened or impaired.
"Poor"	0-44	Water quality departs from its desired levels

performed using SPSS version 21, Past software version 4.11, and Microsoft Office Excel 2019.

RESULTS AND DISCUSSION

Physico-chemical profile of the river water

Different water quality parameters showed seasonal and spatial variation over the period of study. Spatial and seasonal dynamics of the water quality parameters are represented in Table 4 and 5, respectively. The pH of the water samples varied from 6.83 to 8.78, with an average value of 7.62, indicating that the river water samples were slightly alkaline. Similar nature of water in Damodar River was reported by Haldar *et al.* (2014). Water samples of post-monsoon season had higher pH values compared to the other two seasons. Generally, the pH of river water is influenced by the geology of the basin and buffering capacity of water (George *et al.*, 2010). In natural water, pH has a profound impact as it controls the toxicity of various compounds (Ustaoğlu and Tepe, 2019). Electrical conductivity(EC) and total dissolved solids (TDS) are the measures of salinity hazard and determine the aptness of water for irrigational usage (Singh *et al.*, 2020). The capability of an ionic solution to conduct current is known as EC (Haldar *et al.*, 2014). The range of electrical conductivity in Mundeswari River extended from 143 to 962 µs/cm. The EC values remained higher at M3 and M4 sampling stations. Highest EC value was recorded during the pre-monsoon when the river flow was lowest. Minimum EC recorded during monsoon probably due to the effects of monsoon precipitation.EC values change according to the geological settings and amount of precipitation (Ustaoğlu and Tepe, 2019).

The mean TDS value recorded in Mundeswari River was 272.48 mg/L, with minimum and maximum values 78 mg/L and 601 mg/L, respectively. Higher values of TDS were observed at M3 with an average TDS level of 400.5 mg/L. The average TDS level at all the sampling stations was found to be within the permissible limit (500 mg/L). Compared to acidic water, alkaline water contains higher total solids (Haldar *et al.*, 2014).Average TDS values in Mundeswari river were higher than that of Indian average 59 mg/L (Singh *et al.*, 2005). Greater TDS content also entails higher dissolved salt concentration and more hardness in water (Ayogu *et al.*, 2020). Total hardness is owing to the presence of divalent cations and anions. Mostly, it is due to calcium and magnesium ions. The sum of calcium and magnesium hardness is known as total hardness (Khan *et al.*, 2015). Alkalinity is the acid-neutralizing capacity of water (Ustaoğlu and Tepe, 2019). The hardness, alkalinity, calcium, and magnesium concentration in this river ranged from 28.41 mg/L to 244.29 mg/L, 29.8 mg/L to 203.57 mg/L, 4.75 mg/L to 63.77 mg/L and 1.95 mg/L to 29.56 mg/L, respectively. The average level of these parameters remained within their safe limit consistently throughout the study period (Table 3).

Turbidity indicates the cloudiness or murkiness of the water. It is also a measurement of optical property that causes light to be absorbed or scattered by the water (Kothari et al., 2021). Turbidity values in our study displayed an increasing trend from upstream to downstream stations. In this study, turbidity values varied from 8.1 NTU to 220.7 NTU with an average value of 82.09 NTU. Turbidity levels in all the analysed water samples collected from different sampling stations exceeded the maximum permissible limit of 5 NTU (Table 3). During the monsoon, turbidity values were higher irrespective of sampling stations. M4 sampling station (with average turbidity of 122.03 NTU) remained very turbid throughout the period of study, which could be attributed to regular tidal inflow. Dissolved oxygen (DO) is the principal determinant of the ecological health of an aquatic ecosystem (Ustaoğlu and Tepe, 2019).

The mean DO concentration of this river was below 6 mg/L. Spatially lower DO level was observed at M3 and M4 sampling stations; heavy sewage influx could be the possible reason behind it. Low DO value recorded during the low flow period. Barakat *et al.* (2016) hypothesized that poor DO level in pre-monsoon season was linked to high microbial activity and consequent degradation of the organic matter that requires dissolved oxygen. Microbial activity and Biochemical oxygen demand (BOD) get increased during the low flow period accompanied by depletion of DO level in river water. BOD measures the biodegradable portion of the organic pollutants. During the study, BOD was found to be in the range of 0.47 to 8.49 mg/L, with an average of 3.64 mg/L. High BOD value documented at M3 and M4 sampling stations. The average BOD value of this river surpassed the maximum allowed limit of 3 mg/L (Table 3). Higher values of BOD at M3 could be related to the huge organic pollution load. The concentration of nitrate-nitrogen at all the sampling stations, irrespective of season had not exceeded the prescribed permissible limit (50 mg/L).

The measured average nitrate-nitrogen concentration in Mundeswari river was 1.94 mg/L and it fluctuated from 0.21 mg/L to 4.14 mg/L. Nitrate-nitrogen concentration in natural waters usually remain between 1 and 10 mg/L. Nitrate content, as found in this study, is comparatively lower than what reported by George *et al.* (2010) from the upper stretch of Damodar River. As represented in Table 4, the sulphate level in this river varied from 10.42 to 110.45 mg/L, with mean ~42 mg/L. Irrespective of sampling stations and seasons, sulphate level in Mundeswari River were well below 200 mg/L, the permissible limit (Table 3). The main sources of sulphate in the river are bacterial decomposition of sulphur compounds, atmospheric deposition and sulphur containing fertilizers used in the catchment (Şener *et al.*, 2017).

Correlation analysis

Fig. 2 depicts the Pearson correlation matrix that was constructed using twelve water quality attributes. TDS showed a very high positive correlation with EC (r=0.96, P<0.01) and a high correlation with TH (r=0.75, P<0.01), TA (r=0.7, P<0.01) and Ca (r=0.76, P<0.01) and moderate positive correlation with SO_4 (r=0.7, P<0.01) and Mg (r=0.7, P<0.01).EC, TDS, Ca, Mg, SO_4, TH and TA showed a strong positive correlation with each other. These parameters are known to be integrally influenced by each other and indicate their common sources of origin.TH strongly correlated with Ca (r=0.93, P<0.01) and Mg (r=0.84, P<0.01) as Ca and Mg salts contributed to the hardness of the water. The ionic factors mainly influenced EC and TDS are Ca, Mg, SO_4 (Pramanik *et al.*, 2020). Sulphate was moderately correlated with EC, TDS, Ca, Mg and BOD. pH showed a weak correlation with most parameters except DO (r=0.39, P<0.01). Positive correlation between pH and DO was also reported in other studies (Mamun and An, 2021; Mitra *et al.*, 2018). The positive correlation between pH and DO can be explained as such that as the amount of available DO decreases aerobic fermentation process occurs, organic acids are produced and as a result, pH value decreases (Chen *et al.*, 2015; Meng *et al.*, 2020). Nitrate-nitrogen showed a moderate positive correlation with turbidity (r=0.64, P<0.01).

Other investigators also obtained a comparable correlation between nitrate and turbidity (Kothari *et al.*, 2021; Mitra *et al.*, 2018). Turbidity is the most visible indicator of water quality. River water becomes turbid due to the presence of suspended particles which can come from soil erosion, stirred bottom sediments, runoff or algal blooms (Haji Gholizadeh *et al.*, 2016). High nitrate input in the river water column can augment the growth of algae (Haji Gholizadeh *et al.*, 2016). Water sources have become murkier as a result of precipitation runoff and increased soil erosion. Precipitation causes greater loads of soil with high nitrate content in river water; therefore, turbidity and nitrate are connected (Kothari

Table 3. Guideline values of the water quality variables (Akhtar et al., 2021; Hossain & Patra, 2020; World Health Organization, 2018)

Parameter	WHO (2011)	BIS (2012)
TDS (mg/L)	500	500
EC (μs/cm)	750	-
Ca (mg/L)	75	75
Mg (mg/L)	50	50
TH (mg/L)	200	200
TA (mg/L)	-	200
TUR (NTU)	-	<5
pH	6.5-8.5	6.5-8.5
DO (mg/L)	-	>6
BOD (mg/L)	-	<2
NO_3-N (mg/L)	45	45
SO_4 (mg/L)	250	200

Table 4. Spatial dynamics of the water quality variables (Mean ± SD) in Mundeswari River

Parameters	Sampling Stations				Mean	Min	Max
	M1	M2	M3	M4			
pH	7.78± 0.5	7.39 ±0.39	7.58 ±0.44	7.71± 0.46	7.62±0.47	6.83	8.78
TDS	230.71± 77.92	213.71± 88.64	400.5± 143.65	245 ±127.64	272.48±134	78	601
EC	380.5± 128.65	382.29 ±147.6	661.08±213.57	411.63± 215.82	458.88±213.37	143	962
TH	103.95 ±39.61	110.37± 60.58	168.03± 51.55	106.46±43.59	122.2± 55.54	28.41	244.29
TA	107.88 ±38.83	110.26± 54.06	154.03±34.53	111.45±45.46	120.9±47.26	29.8	203.57
Ca	20.02 ±7.89	21.9 ±12.4	36.08 ±13.24	21.65±8.92	24.91±12.51	4.75	63.77
Mg	9.93± 4.37	12.26± 7.4	17.34±6.66	10.37±4.26	12.47± 6.46	1.95	29.56
TUR	54.03 ± 39.08	59.18 ±38.77	93.12±49.89	122.03± 49.82	82.09±51.99	8.1	220.7
DO	6.18± 1.57	6.22 ±1.52	3.93± 1.27	5.9±1.01	5.56±1.64	2.14	9.23
BOD	3±1.27	2.66 ±1.19	5.36 ±1.58	4.59± 1.49	3.9±1.77	0.47	8.49
NO_3-N	1.54± 0.97	1.59±0.86	2.75 ±1.06	2.17± 0.89	2.01±1.06	0.22	5.13
SO_4	37.52 ±16.31	35.91 ±14.51	50.76± 24.7	40.85±28.66	41.26±22.26	7.89	110.45

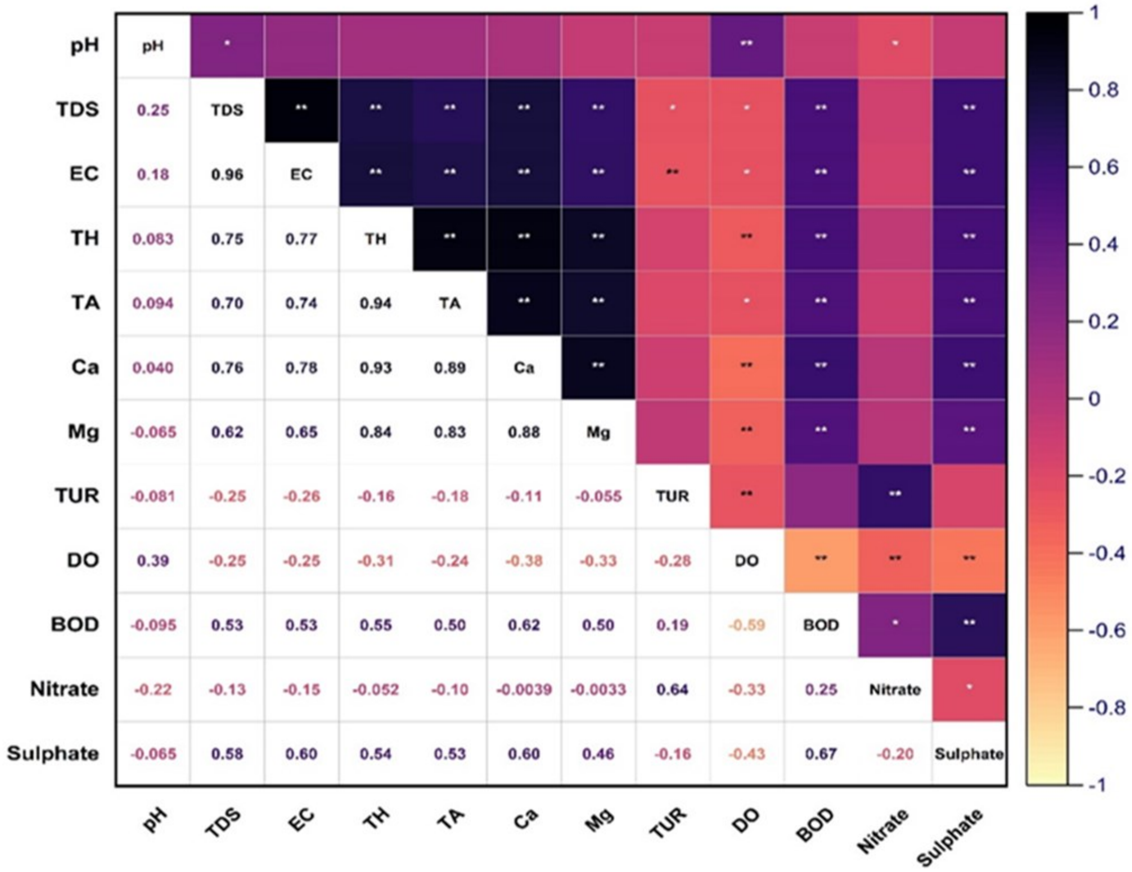

Fig. 2. *Pearson's correlation matrix*

Table 5. Seasonal dynamics of the water quality variables (Mean ± SD) in Mundeswari River

Parameters	PRM	MON	POM
pH	7.45±0.48	7.47±0.34	7.93±0.41
TDS	325.16 ±111.82	149.25 ±68.1	343.03 ±119.21
EC	547.06 ±174.67	263.31 ±120.04	547.06± 187.61
TH	148.29± 54.82	85.72 ±37.25	132.59 ±53.58
TA	142.95 ±42.42	89.04 ±37.11	130.73± 44.92
Ca	31.83 ±13.86	16.96 ±7.73	25.95 ±10.59
Mg	15.47 ±6.97	9.15 ±4.73	12.81 ±6.01
TUR	74.13 ±41.54	120.74 ±51.18	51.4± 36.85
DO	4.33± 1.06	5.36± 1.22	6.99± 1.39
BOD	5.41± 1.65	3.03± 1.37	3.28± 1.21
NO_3-N	1.78± 0.76	2.82± 1.06	1.43± 0.8
SO_4	62.99 ±20.81	22.85± 8.99	37.94 ±12.49

*PRM-pre-monsoon, MON-monsoon, POM-post-monsoon

et al., 2021). DO was somewhat negatively correlated with BOD (r=0.59, P<0.01).Increase in the biodegradation of organic matter could reduce the DO level (Varol, 2020). When organic matter in river water is oxidized at the expense of Dissolved Oxygen, resulting in rise of BOD value and a decrease in DO concentration (Chen *et al.*, 2015).

CCME-WQI

The WQI enables general analysis of the water quality in any aquatic system. WQI indicates the ability of the aquatic system to host aquatic life and also helps to determine whether the overall quality of the riverine system poses potential threats related to multifaceted usage of water(Mamun and An, 2021; Shah and Joshi, 2017). The CCME-WQI was calculated at four sampling stations in the Mundeswari River based on twelve selected water quality parameters. The water quality of most of the monitoring sites based on CCME-WQI values was "marginal." The highest WQI value (82.01) was observed at M1, and the lowest WQI (41.24) was recorded at M3. The one-way ANOVA determined a statistically significant difference in WQI value between sampling sites (P <0.05). According to the Tukey post hoc test, the CCME-WQI value at the M3 sampling site is significantly lower than its two upstream sites. There was no statistically significant difference between M1 and M2 regarding CCME-WQI values (Fig. 3).

The overall WQI value of Mundeswari River during the first year of study, i.e. 2020-21 was 57.54 at M2 and 53.13 at M4, where the water quality received a "marginal" grade. The water quality of M3, with a WQI value of 41.24, is categorized as "poor," and M1, with a WQI value of 65.63, corresponds to "fair" water quality.

Table 6. Estimated CCME-WQI values in Mundeswari River during the study period 2020-22 (PRM: pre-monsoon, MON: monsoon, POM: post-monsoon)

River	Season	Station	2020-21		2021-22	
			WQI	Class	WQI	Class
Mundeswari	PRM	M1	63.71	Marginal	65.63	Fair
		M2	53.54	Marginal	57.54	Marginal
		M3	42.13	Poor	41.24	Poor
		M4	50.34	Marginal	53.13	Marginal
	MON	M1	60.16	Marginal	54.92	Marginal
		M2	62.35	Marginal	54.31	Marginal
		M3	50.79	Marginal	47.47	Marginal
		M4	53	Marginal	50.57	Marginal
	POM	M1	82.01	Good	65.11	Good
		M2	79.34	Good	74.48	Good
		M3	48.45	Marginal	45.31	Marginal
		M4	55.47	Marginal	60.5	Marginal

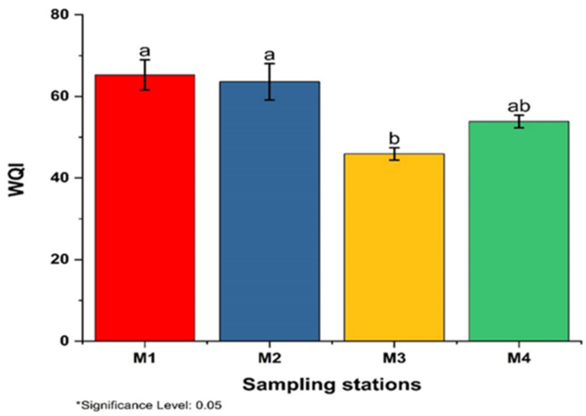

Fig. 3. *CCME-WQI values at different sampling sites of Mundeswari River (different letters indicate statistically significant difference among the sampling sites at P<0.05; Tukey HSD test)*

In 2021-22, computed CCME-WQI values lay between 44.7 and 62.11, representing "marginal" water quality at all the sampling stations (Fig. 4 and Fig. 5). The appended reasons behind the low WQI witnessed at some of the monitoring stations are innumerable anthropogenic activities, including disposal of wastewater from brick fields, residential areas, and commercial establishments; direct or indirect inflow of untreated effluents into the rivers from small-scale industrial clusters and factories located in adjoining areas; and incessant solid waste disposal by local residents living alongside the rivers (Bora and Goswami, 2017; Lee *et al.*, 2020). Fig. 6 shows the dendrogram of cluster analysis constructed to identify the similarities among sampling stations in terms of their water quality status. M1 and M2 stations formed a cluster and had more similarities. As can be seen from Fig. 6, M3 and M4 also formed another cluster.

The CCME-WQI values unveiled that M3 was the most polluted site. In the Mundeswari river, M3 and M4 sites rendered an increased pollution level and consequent decrease in water quality compared to their immediate upstream sites, justified by the demographic pressure and anthropogenic activities. Upstream sites M1 and M2 had relatively better water quality as these sites were located near rural settlements with fewer sources for the influx of pollutants. In M3 sampling station, in addition to waste disposal, high pollution levels may be driven by the stagnancy of water due to lack of sufficient flow (particularly during pre-monsoon), which might reduce the self-purification capability of the river ecosystems (Bora and Goswami, 2017). Analogous impacts on river water quality are also documented in other Indian rivers (Bora and Goswami, 2017; Rehana and Mujumdar, 2011).

Seasonal trends of the CCME-WQI values are depicted in Table 6. In the Mundeswari River, the water quality of the M2 site was categorized as "good" during the post-monsoons of both the years of study. During the post-monsoon season of 2021-22, M1 site attained "good" water quality. During the pre-monsoon, the WQI value of M3 plunged below 44, implying "poor" water quality. Similar tendencies were observed over both years of study (Table 6). Although the WQI values recorded in the Mundeswari River did not exhibit any statistically significant difference (P<0.05) among seasons. Nevertheless, the climatic conditions that prevailed in the study area certainly impacted the water quality of the Mundeswari River. It had putrid water quality before the monsoons and relatively better water quality was evident after the monsoons. This pattern also indicates that disposal of concentrated sewage during the pre-monsoon period without dilution deteriorates the water quality more (Saha *et al.*, 2021). A similar seasonal trend in WQI was reported by Mamun and An (2021) in the Yeongsan River in South Korea; Semy and Singh (2021) in the Tsurang River, and Haldar *et al.*(2014) in the Damodar River in India.

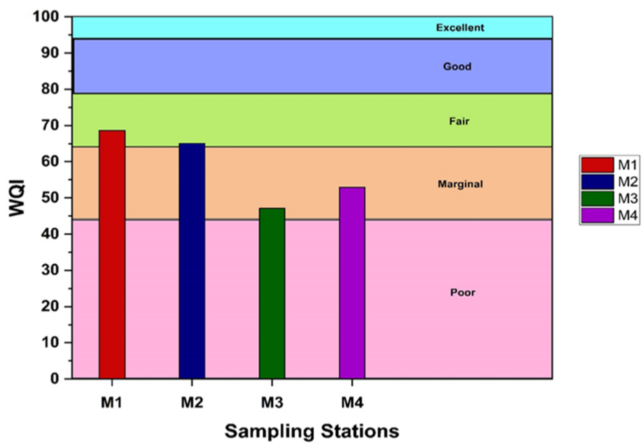

Fig. 4. *Estimated CCME-WQI at different sampling stations (2020-21)*

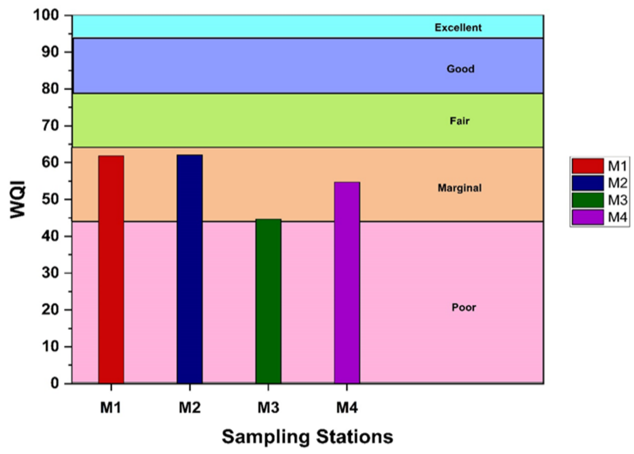

Fig. 5. *Estimated CCME-WQI at different sampling stations (2021-22)*

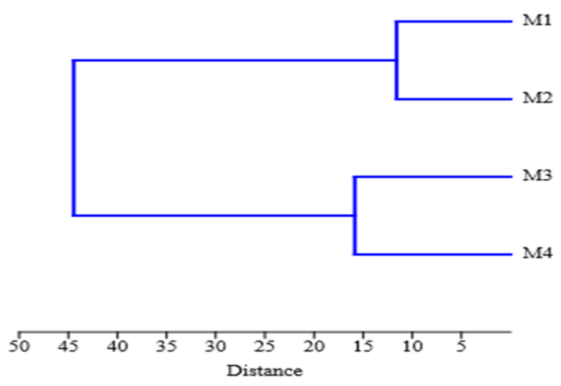

Fig. 6. *Dendrogram showing clusters of sampling stations in Mundeswari River based on CCME-WQI.*

According to the obtained CCME-WQI values, the quality of water in most of the sampling stations of Mundeswari River was unsuitable for direct human usage like drinking; similar results were also obtained in the upper stretch of the Damodar River by other investigators (Mukherjee *et al.*, 2012; Singh *et al.*, 2019). Overall CCME-WQI values ranged from marginal to fair in the Mundeswari River and could pose potential risks based on intended usage. In contrast to results obtained by Haldar *et al.* (2014) in the upper stretch of the Damodar River, which ranged from poor (only one site) to excellent, this study revealed a much grimmer scenario of pollution in the Mundeswari River, where WQI ranged from marginal to fair. Tremendous demographic pressure, coupled with socioeconomic pressure in the form of river bed encroachment, river water exploitation, and sand abstraction for various purposes, has deteriorated the water quality of this river (Bora and Goswami, 2017). The influx of agricultural drainage from the catchment help to develop a eutrophic condition that also worsens the water quality. However, it can be noted that Mundeswari River water quality is closer to the Nile River, as reported by Abdel-Satar *et al.* (2017), and better than the Coruh River and Surma River, as reported by Bilgin (2018) and Munna *et al.* (2013) respectively.

Conclusion

The present study concluded that the quality status Mundeswari River indicated a significant spatial heterogeneity as well as seasonal differences in water quality parameters. The Mundeswari River is vulnerable to pollution, as some of the water quality parameters exceeded their standard acceptable limits. The water quality of most monitoring sites based on CCME-WQI values was "marginal." Seasonal variation in CCME-WQI values was also pronounced. The water quality of the Mundeswari River worsened before the arrival monsoon but improved somewhat following the monsoon. This investigation indicated that this river water is unfit for human consumption and requires considerable treatment before being used for domestic purposes. Water quality of this river needs to be restored by implementing measures like restricting the inflow of raw domestic sewage and dumping of solid wastes. The baseline data generated during this study could provide insight to the policymakers and environmental managers if any action plans are taken to better manage this socioeconomically vital riverine system.

Conflict of interest

The authors declare that they have no conflict of interest.

REFERENCES

1. Abbasi, T. & Abbasi, S. A. (2012). Water-Quality Indices: Looking Back, Looking Ahead In: *Water Quality Indices* (pp 353–356). Elsevier, Amsterdam. https://doi.org/10.1016/B978-0-444-54304-2.00016-6
2. Abdel-Satar, A. M., Ali, M. H. & Goher, M. E. (2017). Indices of water quality & metal pollution of Nile River, Egypt. *The Egyptian Journal of Aquatic Research*, 43(1), 21–29. https://doi.org/10.1016/j.ejar.2016.12.006
3. Akhtar, N., Ishak, M. I. S., Ahmad, M. I., Umar, K., Md Yusuff, M. S., Anees, M. T. … Ali Almanasir, Y. K. (2021). Modification of the Water Quality Index (WQI) Process for Simple Calculation Using the Multi-Criteria Decision-Making (MCDM) Method: A Review. *Water*, 13(7), 905. https://doi.org/10.3390/w13070905
4. American Public Health Association (2017). Standard methods for the examination of water and wastewater. 23rd Ed. American Water Works Association, Washington DC, USA.
5. Ayogu, C. N., Maduka, R. I., Ayogu, N. O., Njoku, C. N. & Chinedu-Asogwa, N. C. (2020). Hydro-geochemical analysis & quality evaluation of surface water in the Mamu River basin, southeastern Nigeria. *Applied Water Science*, 10 (7), 159. https://doi.org/10.1007/s13201-020-01247-7
6. Barakat, A., El Baghdadi, M., Rais, J., Aghezzaf, B. & Slassi, M. (2016). Assessment of spatial and seasonal water quality variation of Oum Er Rbia River (Morocco) using multivariate statistical techniques. *International Soil and Water Conservation Research*, 4(4), 284–292. https://doi.org/10.1016/j.iswcr.2016.11.002
7. Bilgin, A. (2018). Evaluation of surface water quality by using Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) method and discriminant analysis method: A case study Coruh River Basin. *Environmental Monitoring and Assessment*, 190(9), 554. https://doi.org/10.1007/s10661-018-6927-5
8. Bora, M. & Goswami, D. C. (2017). Water quality assessment in terms of water quality index (WQI): Case study of the Kolong River, Assam, India. *Applied Water Science*, 7 (6), 3125–3135. https://doi.org/10.1007/s13201-016-0451-y
9. Chen, P., Li, L. & Zhang, H. (2015). Spatio-Temporal Variations and Source Apportionment of Water Pollution in

Danjiangkou Reservoir Basin, Central China. *Water*, 7(6), 2591–2611. https://doi.org/10.3390/w7062591
10. Cho, Y.-C., Choi, H., Lee, M.-G., Kim, S.-H. & Im, J.-K. (2022). Identification and Apportionment of Potential Pollution Sources Using Multivariate Statistical Techniques & APCS-MLR Model to Assess Surface Water Quality in Imjin River Watershed, South Korea. *Water*, 14(5), 793. https://doi.org/10.3390/w14050793
11. Chou, J.-S., Ho, C.-C. & Hoang, H.-S. (2018). Determining quality of water in reservoir using machine learning. *Ecological Informatics*, *44*, 57–75. https://doi.org/10.1016/j.ecoinf.2018.01.005
12. Choudhury, M., Pervez, A., Sharma, A. & Mehta, J. (2022). Human-induced stresses on the rivers beyond their assimilation and regeneration capacity In: *Ecological Significance of River Ecosystems* (pp 281–298). Elsevier. https://doi.org/10.1016/B978-0-323-85045-2.00019-4
13. George, J., Thakur, S. K., Tripathi, R. C., Ram, L. C., Gupta, A. & Prasad, S. (2010). Impact of coal industries on the quality of Damodar river water. *Toxicological and Environmental Chemistry*, 92(9), 1649–1664. https://doi.org/10.1080/02772241003783737.
14. Ghosh, P. & Panigrahi, A. K. (2018). A comprehensive study on correlation of gastropod diversity with some hydroenvironmental parameters of selected waterbodies of lower Damodar basin, West Bengal, India. *Journal of Applied and Natural Science*, 10(4), 1259–1265. https://doi.org/10.31018/jans.v10i4.1933
15. Gitau, M. W., Chen, J. & Ma, Z. (2016). Water Quality Indices as Tools for Decision Making and Management. *Water Resources Management*,30(8),2591–2610. https://doi.org/10.1007/s11269-016-1311-0
16. Gupta, S. & Gupta, S. K. (2021). A critical review on water quality index tool: Genesis, evolution and future directions. *Ecological Informatics*,63,101299. https://doi.org/10.1016/j.ecoinf.2021.101299
17. Haji Gholizadeh, M., Melesse, A. M. & Reddi, L. (2016). Water quality assessment and apportionment of pollution sources using APCS-MLR and PMF receptor modeling techniques in three major rivers of South Florida. *Science of The Total Environment*, 566–567, 1552–1567. https://doi.org/10.1016/j.scitotenv.2016.06.046
18. Haldar, D., Halder, S., Das, P. & Halder, G. (2014). Assessment of water quality of Damodar River in South Bengal region of India by Canadian Council of Ministers of Environment (CCME) Water Quality Index: A case study. *Desalination and Water Treatment*, 1–14. https://doi.org/10.1080/19443994.2014.987168
19. Hamlat, A., Guidoum, A. & Koulala, I. (2016). Status and trends of water quality in the Tafna catchment: A comparative study using water quality indices. *Journal of Water Reuse and Desalination*, 7(2), 228–245. https://doi.org/10.2166/wrd.2016.155
20. Hassan, F., Shaawiat, A. & Al Obaidy, A. H. (2018). Evaluation of Al-Shamiyah River water quality using the Canadian Council of Ministries of the Environment (CCME) water quality index and factor analysis. *Desalination and Water Treatment*, 116, 342–348. https://doi.org/10.5004/dwt.2018.22553
21. Hossain, M. & Patra, P. K. (2020). Water pollution index – A new integrated approach to rank water quality. *Ecological Indicators*, 117,106668. https://doi.org/10.1016/j.ecolind.2020.106668
22. Khan, M. Y. A., Gani, K. M. & Chakrapani, G. J. (2015). Assessment of surface water quality and its spatial variation. A case study of Ramganga River, Ganga Basin, India. *Arabian Journal of Geosciences*, 9(1), 28. https://doi.org/10.1007/s12517-015-2134-7
23. Kothari, V., Vij, S., Sharma, S. & Gupta, N. (2021). Correlation of various water quality parameters & water quality index of districts of Uttarakhand. *Environmental and Sustainability Indicators*, 9, 100093. https://doi.org/10.1016/j.indic.2020.100093
24. Lee, K.-H., Kang, T.-W., Ryu, H.-S., Hwang, S.-H. & Kim, K. (2020). Analysis of spatiotemporal variation in river water quality using clustering techniques: A case study in the Yeongsan River, Republic of Korea. *Environmental Science and Pollution Research*, 27(23), 29327–29340. https://doi.org/10.1007/s11356-020-09276-0
25. Lumb, A., Sharma, T. C. & Bibeault, J.-F. (2011). A Review of Genesis and Evolution of Water Quality Index (WQI) and Some Future Directions. *Water Quality, Exposure and Health*, *3*(1), 11–24. https://doi.org/10.1007/s12403-011-0040-0
26. Mamun, M. & An, K.-G. (2021). Application of Multivariate Statistical Techniques & Water Quality Index for the Assessment of Water Quality and Apportionment of Pollution Sources in the Yeongsan River, South Korea. *International Journal of Environmental Research and Public Health*, 18(16), 8268. https://doi.org/10.3390/ijerph18168268
27. Marselina, M., Wibowo, F. & Mushfiroh, A. (2022). Water quality index assessment methods for surface water: A case study of the Citarum River in Indonesia. *Heliyon*, 8 (7), e09848. doi: 10.1016/j.heliyon.2022.e09848
28. Matta, G., Nayak, A., Kumar, A. & Kumar, P. (2020). Water quality assessment using NSFWQI, OIP and multivariate techniques of Ganga River system, Uttarakhand, India. *Applied Water Science*, 10(9), 206. https://doi.org/10.1007/s13201-020-01288-y
29. Meng, C., Song, X., Tian, K., Ye, B. & Si, T. (2020). Spatiotemporal Variation Characteristics of Water Pollution & the Cause of Pollution Formation in a Heavily Polluted River in the Upper Hai River. *Journal of Chemistry*, 2020, 1–15. https://doi.org/10.1155/2020/6617227
30. Mitra, S., Ghosh, S., Satpathy, K. K., Bhattacharya, B. D., Sarkar, S. K., Mishra, P. & Raja, P. (2018). Water quality assessment of the ecologically stressed Hooghly River Estuary, India: A multivariate approach. *Marine Pollution Bulletin*, 126, 592–599. https://doi.org/10.1016/j.marpolbul.2017.09.053
31. Mukate, S., Wagh, V., Panaskar, D., Jacobs, J. A. & Sawant, A. (2019). Development of new integrated water quality index (IWQI) model to evaluate the drinking suitability of water. *Ecological Indicators*, 101, 348–354. https://doi.org/10.1016/j.ecolind.2019.01.034
32. Mukherjee, D., S Lata Dora, R. T. & Tiwary,R.K. (2012). Evaluation of Water Quality Index For Drinking Purposes In The Case of Damodar River, Jharkhand and West Bengal Region, India. *Journal of Bioremediation and Biodegradation*, 03(09). https://doi.org/10.4172/2155-6199.1000161
33. Munna, G. M., Chowdhury, M. M. I., Ahmed, A. A. M. & Chowdhury, S. (2013). A Canadian Water Quality Guideline-Water Quality Index (CCME-WQI) based assessment

study of water quality in Surma River. *Journal of Civil Engineering and Construction Technology*, 4(3), 81–89. https://doi.org/10.5897/JCECT12.074

34. Najah Ahmed, A., Binti Othman, F., Abdulmohsin Afan, H., Khaleel Ibrahim, R., Ming Fai, C., Shabbir Hossain, M. … Elshafie, A. (2019). Machine learning methods for better water quality prediction. *Journal of Hydrology*, 578, 124084. https://doi.org/10.1016/j.jhydrol.2019.124084
35. Panagopoulos, Y., Alexakis, D. E., Skoulikidis, N. T., Laschou, S., Papadopoulos, A. & Dimitriou, E. (2022). Implementing the CCME water quality index for the evaluation of the physicochemical quality of Greek rivers. *Water*, 14(17), 2738. doi: 10.3390/w14172738
36. Pramanik, A. K., Majumdar, D. & Chatterjee, A. (2020). Factors affecting lean, wet-season water quality of Tilaiya reservoir in Koderma District, India during 2013–2017. *Water Science*, 34, 85–97. https://doi.org/10.1080/11104929.2020.1765451
37. Regmi, R. K., Mishra, B. K., Masago, Y., Luo, P., Toyozumi-Kojima, A. & Jalilov, S.-M. (2017). Applying a water quality index model to assess the water quality of the major rivers in the Kathmandu Valley, Nepal. *Environmental Monitoring and Assessment*, 189(8), 382. https://doi.org/10.1007/s10661-017-6090-4
38. Rehana, S. & Mujumdar, P. P. (2011). River water quality response under hypothetical climate change scenarios in Tunga-Bhadra river, India. *Hydrological Processes*, 25 (22), 3373–3386. https://doi.org/10.1002/hyp.8057
39. Saha, A., Ramya, V. L., Jesna, P. K., Mol, S. S., Panikkar, P., Vijaykumar, M. E. … Das, B. K. (2021). Evaluation of Spatio-temporal Changes in Surface Water Quality and Their Suitability for Designated Uses, Mettur Reservoir, India. *Natural Resources Research*, 30(2), 1367–1394. https://doi.org/10.1007/s11053-020-09790-5
40. Sanyal, J., Carbonneau, P. & Densmore, A. L. (2014). Low-cost inundation modelling at the reach scale with sparse data in the Lower Damodar River basin, India. *Hydrological Sciences Journal*, 59(12), 2086–2102. https://doi.org/10.1080/02626667.2014.884718
41. Semy, K. & Singh, M. R. (2021). Quality assessment of Tsurang River water affected by coal mining along the Tsurangkong Range, Nagaland, India. *Applied Water Science*, 11(7), 115. https://doi.org/10.1007/s13201-021-01444-y
42. Şener, Ş., Şener, E. & Davraz, A. (2017). Evaluation of water quality using water quality index (WQI) method and GIS in Aksu River (SW-Turkey). *Science of The Total Environment*, 584–585, 131–144. https://doi.org/10.1016/j.scitotenv.2017.01.102
43. Shah, K. A. & Joshi, G. S. (2017). Evaluation of water quality index for River Sabarmati, Gujarat, India. *Applied Water Science*, 7(3), 1349–1358. https://doi.org/10.1007/s13201-015-0318-7
44. Sharma, D. & Kansal, A. (2011). Water quality analysis of River Yamuna using water quality index in the national capital territory, India (2000–2009). *Applied Water Science*, 1(3), 147–157. https://doi.org/10.1007/s13201-011-0011-4
45. Singh, K. K., Tewari, G. & Kumar, S. (2020). Evaluation of Groundwater Quality for Suitability of Irrigation Purposes: A Case Study in the Udham Singh Nagar, Uttarakhand. *Journal of Chemistry*, *2020*, e6924026. https://doi.org/10.1155/2020/6924026
46. Singh, K. P., Malik, A. & Sinha, S. (2005). Water quality assessment & apportionment of pollution sources of Gomti river (India) using multivariate statistical techniques—A case study. *Analytica Chimica Acta*, 538(1),355–374. https://doi.org/10.1016/j.aca.2005.02.006
47. Singh, R., Chaturvedi, A. & Kumari, K. (2019). Water-quality assessment of Damodar River and its tributaries & subtributaries in Dhanbad Coal mining areas of India based on WQI. *Sustainable Water Resources Management*, 5(2),381–386. https://doi.org/10.1007/s40899-017-0159-7
48. Singh, R., Villuri, V., Pasupuleti, S. & Nune, R. (2020). Hydrodynamic modeling for identifying flood vulnerability zones in lower Damodar river of eastern India. *Ain Shams Engineering Journal*, 11. https://doi.org/10.1016/j.asej.2020.01.011
49. Terrado, M., Barceló, D., Tauler, R., Borrell, E., Campos, S. de & Barceló, D. (2010). Surface-water-quality indices for the analysis of data generated by automated sampling networks. *Trends in Analytical Chemistry*, 29(1),40–52. https://doi.org/10.1016/j.trac.2009.10.001
50. Uddin, Md. G., Nash, S. & Olbert, A. I. (2021). A review of water quality index models and their use for assessing surface water quality. *Ecological Indicators*, 122, 107218. https://doi.org/10.1016/j.ecolind.2020.107218
51. Ustaoğlu, F. & Tepe, Y. (2019). Water quality & sediment contamination assessment of Pazarsuyu Stream, Turkey using multivariate statistical methods and pollution indicators. *International Soil and Water Conservation Research*,*7*(1),47–56. https://doi.org/10.1016/j.iswcr.2018.09.001
52. Varol, M. (2020). Use of water quality index and multivariate statistical methods for the evaluation of water quality of a stream affected by multiple stressors: A case study. *Environmental Pollution*, 266, 115417. https://doi.org/10.1016/j.envpol.2020.115417
53. Verma, R. K., Murthy, S., Tiwary, R. K. & Verma, S. (2019). Development of simplified WQIs for assessment of spatial and temporal variations of surface water quality in upper Damodar river basin, eastern India. *Applied Water Science*, 9(1), 21. https://doi.org/10.1007/s13201-019-0893-0
54. von Schiller, D., Acuña, V., Aristi, I., Arroita, M., Basaguren, A., Bellin, A. … Elosegi, A. (2017). River ecosystem processes: A synthesis of approaches, criteria of use and sensitivity to environmental stressors. *Science of The Total Environment*, *596–597*, 465–480. https://doi.org/10.1016/j.scitotenv.2017.04.081
55. World Health Organization (2018). *Guidelines for Drinking-water Quality* (4th ed.). Geneva: World Health Organization. Retrieved from https://apps.who.int/iris/h&le/10665/276001
56. Yotova, G., Varbanov, M., Tcherkezova, E. & Tsakovski, S. (2021). Water quality assessment of a river catchment by the composite water quality index & self-organizing maps. *Ecological Indicators*, 120, 106872. https://doi.org/10.1016/j.ecolind.2020.106872