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Original Articles

Development of entropy and deviation-based water quality index: Case of river Ganga, India

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ABSTRACT

In this study, a comprehensive multiplicative water quality index, M_{ED}-WQI, for surface water quality assessment has been developed that uses sub-index functions based on deviation from maximum contaminant level of respective parameters. The parametric weights in M_{ED}-WQI were computed using entropy based approach to eliminate subjectivity. Using a synthetic dataset the performance of M_{ED}-WQI has been compared with Composite WQI (CWQI) that is based on Saaty's analytical hierarchical process. The results indicated that in comparison to CWQI, M_{ED}-WQI approach provides an objective and rational framework that eliminates clustering effect in providing the water quality status. Further, M_{ED}-WQI has been applied to an exhaustive water quality dataset of river Ganga, one of the major perennial rivers of India. Out of 224 sampling locations, 167 sites have been associated with excellent or good water quality class whereas 57 sites are identified with either fair, poor, or heavily-polluted water quality class. Furthermore, the water quality classes correlated well with the type of anthropogenic activities carried out at the site.

1. Introduction

Rivers are an essential source of fresh water that harboured many human settlements and supported ancient civilizations to thrive on their basins. Globally, the total water consumption toward various human activities has been reported to be 8442 km^3/yr (Wu et al., 2022). Over the years, due to over-exploitation of this limited water resource had resulted in pollution of this essential life-supporting resource. Due to rapid industrialization, urbanization, and other unsustainable developmental activities the surface water quality has deteriorated in many perennial rivers viz. Ganga, Yellow river, Citarum, Meckong river, Indus, etc. across the world (Kaushal et al., 2019). Hence monitoring of river water quality is of paramount importance. The assessment of surface water quality is a prerequisite for implementation of water protection policies and optimal allocation of water resources towards its intended uses (Shah and Joshi, 2017).

Typically, the status of surface water quality is assessed by measuring several important water quality parameters viz. pH, turbidity, dissolved oxygen, etc. The overall quality status of surface water is hardly perceived through the variations in the individually measured water quality parameters. To address this lacuna, researchers in the past have developed the paradigm of Water Quality Index (WQI). WQI provides a framework for arriving at a unique qualitative indicator of water quality status. WQI reflects the composite effect of different parameters that are considered to represent the overall water quality (Wu et al., 2018). Many water quality indices have been developed in the last 50 years. Some of the widely used water quality indices include Canadian Council of Ministers of the Environment Water Quality Index (CCME-WQI), National Sanitation Foundation's (NSF) Additive Water Quality Index (AWQI) and Multiplicative Water Quality Index (MWQI), Oregon Water Quality Index (OWQI) (Lumb et al., 2011). These WQI's not only provide information about water quality but also enables tracking of the spatial and temporal changes in water quality (Sarkar and Majumder, 2021). Many researchers have used these WQI's for their studies depending on their specific objectives of water use (Sargaonkar and Deshpande, 2003; Abbasi and Abbasi, 2012; Wu et al., 2018).

CCME-WQI was developed to provide a qualitative indication of water quality towards conservation of aquatic life. CCME-WQI requires at least four parameters sampled at four different seasons to determine the value of WQI which makes it a data-intensive approach. A major limitation of this method is the assignment of equal weights to all parameters (Marine, 1999). In the case of NSF's-AWQI, the number and chosen set of water quality parameters can vary and are dependent on the following viz. study objectives, ease of sampling, availability of data,

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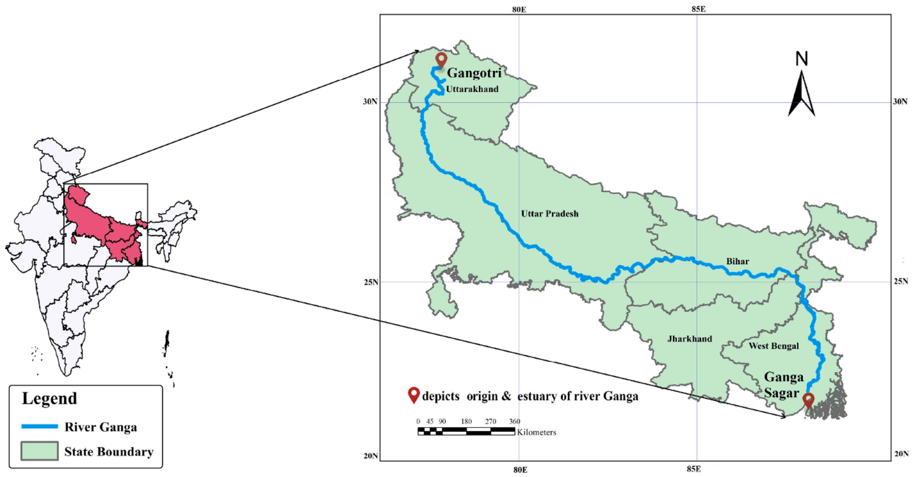

Fig. 1. Course of river Ganga through various states of India.

nature of water use etc. The mode of aggregation in AWQI is based on arithmetic averaging due to which AWQI is less sensitive and provide similar index score when only few water quality parameters vary hugely (Brown et al., 1970; Brown et al., 1973). On the contrary, NSF's-MWQI uses geometric averaging as a mode of aggregation and it is more sensitive in capturing the effect of huge variation when only few parameters vary. One of the major limitations with geometric averaging is noticed when the value of just one parameter is close to zero then the WQI tend to be zero (Mophin-Kani and Murugesan, 2011; Kachroud et al., 2019). In the case of OWQI, harmonic averaging is used as the mode of aggregation wherein sub-index values with equal weights is assigned to all parameters (Cude, 2001). In comparison to AWQI and MWQI, OWQI would depict water quality status in the lowest class (Lumb et al., 2011). One of the major limitations in this method is the assignment of equal weights to all parameters. Also, due to harmonic averaging, the anomalies in the measurement of water quality parameters will be captured in the final WQI (Kachroud et al., 2019).

Singh et al. (2019) have proposed a CWQI based on arithmetic-weighted aggregation using 25 parameters wherein sub-indices are either linear functions or constant values. In this approach, Saaty's Analytical Hierarchy Process (AHP) method was adopted for assignment of relative weights and calculation of WQI (Saaty, 1980). Mukherjee et al. (2017) have used a similar arithmetic-weighted approach along with AHP method. In contrast to Singh et al. (2019) the latters approach involved calculation of sub-indices that are estimated by measuring deviation of water quality parameters from standard values. The standard values are the Maximum Contaminant Level (MCL) provided by various regulatory organizations viz. Bureau of Indian Standards (BIS), Central Pollution Control Board (CPCB), World Health Organization (WHO), United States Environmental Protection Agency (USEPA) etc. In both Singh et al. (2019) and Mukherjee et al. (2017) studies, the AHP method required assignment of weights by expert judgement (Delphi technique) which are expected to be based on the importance of individual parameter towards the intended water use viz. irrigation, drinking, aquatic life etc. (Goodman, 1987). In order to eliminate the subjectivity in assignment of weights in earlier methods, the entropy-based method was used by Gorgij et al. (2017) and Singh et al. (2020) that captured the inherent randomness of the parameters.

In this study, the proposed objectives are (i) To develop a multiplicative water quality index, M_{ED}-WQI, that uses entropy-based weights assignment wherein parameter-wise sub-index functions have been formulated using deviation from MCL. (ii) To evaluate the performance of M_{ED}-WQI in comparison to the existing CWQI method using a synthetic dataset. (iii) To assess the water quality status of river Ganga, one of the major perennial rivers of India using M_{ED}-WQI.

2. Materials and methods

2.1. Synthetic dataset

To evaluate the performance of proposed M_{ED}-WQI, a synthetic dataset has been used that comprise of 60 samples with six water quality parameters viz. pH, hardness, chloride, fluoride, total dissolved solids (TDS) and turbidity. The 60 samples were arrived by combining 4 categories of having 15 samples each. The first 15 set of samples had all the water quality parameters within the MCL. Whereas, the second and third sets of 15 samples had water quality parameters containing moderate exceedance in MCL. The fourth set of 15 samples had the highest exceedance in MCL (i.e. 5 times the MCL) representing a highly polluted scenario. The details of synthetic dataset are provided in supplementary information (Table SI1).

2.2. Study area

The river Ganga originates at Goumukh glacier at an elevation of 3892 m in Uttarakhand state of India. It drains into the Bay of Bengal at the estuary point Ganga Sagar, after traversing 2525 km through five states viz. Uttarakhand, Uttar Pradesh, Bihar, Jharkhand, and West Bengal (Fig. 1). The course of river Ganga through the Himalyan region toward southeast vast plains was shown using a digital elevation model by Elbeltagi et al. (2021). The Ganga river basin covers 11 states of India and is the largest river basin of India. About 40% of country's population is dependant on river Ganga for their domestic and agricultural activities (Kaushal et al., 2019; Elbeltagi et al., 2021).

For decades, river Ganga has been the subject of national and international studies that are mostly aimed at determining its origins and effects of increased anthropogenic activity on river water quality (Bhutiani et al., 2016; Kaushal et al., 2019). The Ganga river basin was relatively free of anthropocentric activity until 1940s. In the recent past, it has became a receptor of pollutants from agricultural, industrial, sewage wastes, cultural, religious tourism etc. Owing to growing population and increasing urbanization (Bhutiani et al., 2016; Kamboj et al., 2019).

2.3. Sample collection and analysis

In this study, water samples were collected from the whole stretch of river Ganga, i.e. from Gangotri in the upper Himalayas to Ganga Sagar, covering about 2510 km of the distance along the river (Fig. 1.) The collection of samples started as a part of pollution mapping activity carried out by Atulya Ganga Trust during walking along with river Ganga (Parikrama) from December 2020 to June 2021. The one-time

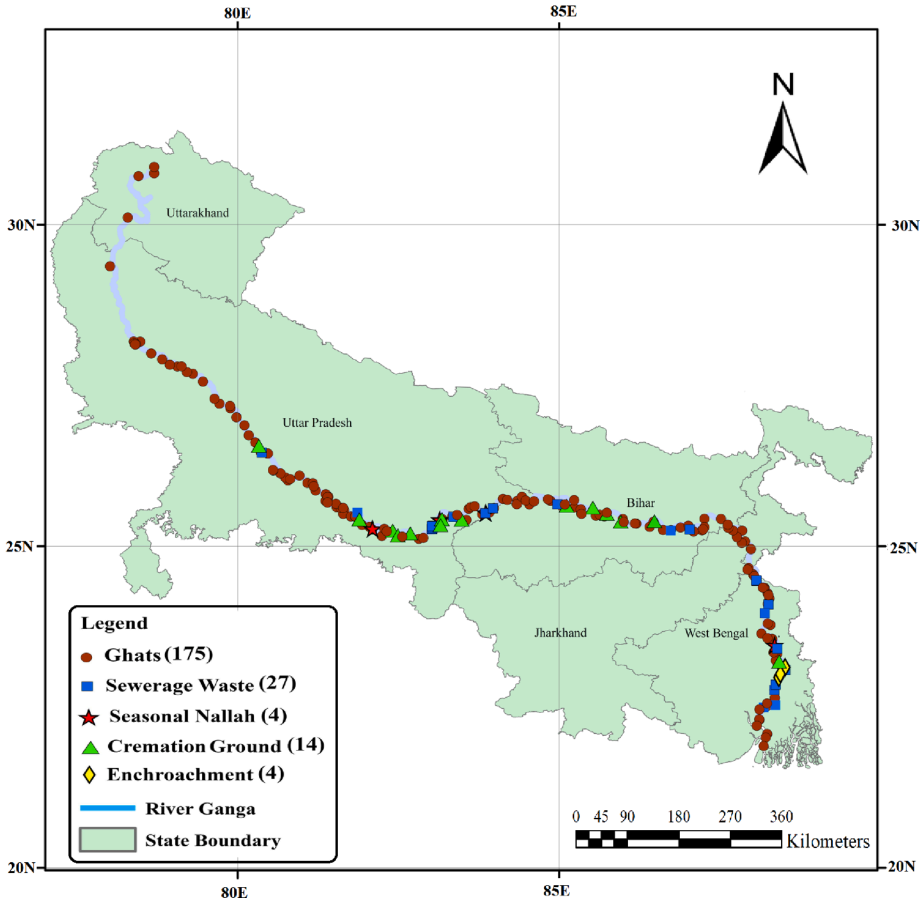

Fig. 2. Details of sampling points along river Ganga.

sampling event started from Prayagraj town in Uttar Pradesh state and subsequently covered other four states viz. Bihar, Jharkhand, West Bengal, and Uttrakhand. The exact date, geographical coordinates, and location of sample collection for each site has been presented in Table SI2. Due to the prevailing Covid-19 pandemic, each sample could be collected once during the study period. Also, as a result of Covid-19 scenario the amount of pollution in river stream is expected to be lower then the usual pollution levels primarily due to lock down of industries (Chakraborty et al., 1197).

In this sampling exercise, a total of 224 surface water samples were collected (Table SI2). The sampling sites along the river are chosen based on anthropogenic activity potential and socioeconomic significance. Out of a total of 224 samples, 175 samples were collected near river ghats where various human activities along the water-body is dominant. 27 samples were collected near sewage disposal points along the river course. 14 samples were collected near cremation grounds along the river banks. 4 samples were collected near encroachment areas where various man-made activities like bathing, washing clothes etc. are contributing to pollution. 4 samples were collected near seasonal nallahs where surface runoff drains into the river during the rainy season. The geographical coordinates of the sampling domain lies between 21°53’ 43” N to 30°59’ 30” N and 78°00’ 51” E to 88°28’ 06” E as shown in Fig. 2.

The sampling location details were recorded using a mobile application that used Global Positioning System (GPS) interfacing and all the information pertaining to the samples were saved on a cloud server (Verma and Sharma, 2022).The sampling locations and water quality status maps are prepared using ArcGIS 10.4 software.

The samples were collected following the standard methods for examination of water and wastewater (APHA, 2012). Briefly, duplicate samples were collected in a wide mouthed 1000 mL HDPE bottle from the center of the river at a depth of roughly 2 feet below the surface. Before sample collection, the sampling bottles were filled and rinsed three times using the water to be sampled.

In-situ parameters like DO and temperature are measured using Lutron DO-5509 meter and a digital thermometer, respectively. The accuracy of DO meter and digital thermometer are $\pm 0.1 mgL^{-1}$ and $\pm 0.1^{\circ}$C, respectively. The pH measurements were done by HM digital pH-80 pen-type pH meter (accuracy ±0.1) with calibration performed after every 20 samples using standard buffer solutions (pH 4, 7, and 10). TDS was measured using HM COM80 digital TDS meter (accuracy ±0.1 mg/L). Turbidity, hardness, chlorides, and fluorides were measured using Transchem™ multi-parameter kit that was pre-calibrated as per IS code in the laboratory before using in the field. The accuracy of these parameters are ±1 NTU, $\pm 0.5 mgL^{-1}$ of $CaCO_3$, $\pm 1 mgL^{-1}$ and $\pm 0.1 mgL^{-1}$, respectively. All the parameters were measured in duplicates and the average value has been used for WQI calculations.

2.4. Methodology

The methodology adopted for developing the M_{ED}-WQI, is as follows: (i) Selection of the water quality parameters. (ii) Developing sub-indices functions (S_i). (iii) Estimation of relative weights using entropy method. (iv) Multiplicative aggregation of sub-indices to estimate M_{ED}-WQI. (v) Implementation of M_{ED}-WQI in visual basic based spreadsheet program. (vi) Comparison of M_{ED}-WQI with CWQI of Singh et al. (2019).

2.4.1. Selection of water quality parameters

In India, BIS and CPCB standards govern the acceptable limits of water quality parameters for various purposes. For using surface water for various purposes BIS (IS2296: 1992) have provided several classes

Table 1
Parametric deviation and the corresponding sub-indices scores in M_{ED}-WQI.

Parameter	(Units)	MCL IS2296/USEPA*	Sub-indices scores				
			[100,60]	[60,35]	[35,15]	[15,5]	[5,0]
pH		6.5–8.5	[0,0.2]	[0.2,0.5]	[0.5,0.8]	[0.8,1.2]	>1.2
Hardness	(mg/L)	300	[0,75]	[75,150]	[150,225]	[225,300]	>300
Chloride	(mg/L)	250	[0,150]	[150,300]	[300,450]	[450,600]	>600
Fluoride	(mg/L)	1.5	[0,0.3]	[0.3,0.6]	[0.6,0.9]	[0.9–1.2]	>1.2
DO	(mg/L)	6.0	[0,0.8]	[0.8,1.6]	[1.6,2.4]	[2.4,3.2]	>3.2
TDS	(mg/L)	500	[0,600]	[600,1200]	[1200,1800]	[1800,2400]	>2400
Turbidity	(NTU)	10*	[0,10]	[10,20]	[20,30]	[30,40]	>40

Note: S_i value will be 100 when parameter value is within MCL.

Table 2
Sub-index scores and corresponding sub-index functions (S_i) for various parameters.

Parameters	Unit	S_i Functions				
		[100,60]	[60,35]	[35,15]	[15,5]	[5,0]
pH (< 6.5)		y = 200x-1200	y = 83.33x-465	y = 66.67x-365	y = 33.33x-175	y = 16.67x-85
pH (> 8.5)		y = −200x + 1800	y = −83.33x + 785	y = −66.67x + 635	y = −33.33x + 325	y = −16.67x + 166.67
Hardness	mg/L	y = −0.53x + 250	y = −0.33x + 185	y = −0.267x + 155	y = −0.133x + 85	y = −0.007x + 9.28
Chlorides	mg/L	y = −0.267x + 167.67	y = −0.167x + 126.8	y = −0.133x + 108.33	y = −0.067x + 61.66	y = −0.0021x + 6.72
Fluoride	mg/L	y = −133.33x + 300	y = −83.33x + 210	y = −66.67x + 175	y = −33.33x + 95	y = −16.67x + 50
DO	mg/L	y = 50x-200	y = 31.25x-102.5	y = 25x-75	y = 12.5x-30	y = 2.08x-0.8
TDS	mg/L	y = −0.066x + 133.33	y = −0.041x + 105.83	y = −0.033x + 91.66	y = −0.0167x + 53.33	y = −0.0022x + 11.6
Turbidity	NTU	y = −4x + 140	y = −2.5x + 110	y = −2x + 95	y = −x + 55	y = −0.038x + 6.93

Note: S_i value will be 100 when parameter value is within MCL.

viz. drinking water (Class-A), water for outdoor bathing (Class-B), drinking water with treatment (Class-C), fish culture and wild life (Class-D) and water for irrigation and industrial use (Class-E). In this study, six of the seven surface water quality parameters viz. pH, hardness, chloride, fluoride, TDS, and DO have been compared with drinking water quality-class(A) established by CPCB and BIS (IS2296:1992). In case of turbidity, USEPA's drinking water standard has been considered due to its non-availability of standard limits for turbidity in CPCB and BIS (IS2296:1992). These parameters were chosen for assessing surface water quality in earlier studies as well (Kumar and Dua, 2009; Singh et al., 2015).

2.4.2. *Development of rating scale and sub-index functions* (S_i)

Rating scale

A rating scale of 0 to 100 is proposed for the sub-indices scores where 0 represents the worst quality scenario and 100 represents excellent water quality scenario. To rate the surface water quality, a deviation-based approach has been adopted (Mukherjee et al., 2017). In this approach, the deviation value (D_i) is calculated by finding the difference between measured value of chosen water quality parameter from its corresponding MCL. The deviation values are categorised into five ranges with uniform intervals for all parameters except for pH. Based on the magnitude of parametric deviation, appropriate rating scale is assigned viz. 100–60, 60–35, 35–15, 15–5 or 5–0. These categories for sub-indices scores are considered with the penalty based approach, wherein higher deviation would result in lower rating.

Deviation value of a parameter is defined as:-

$$D_i = |D_p - D_d| \tag{1}$$

Where D_i is the deviation of a parameter considered, D_p is the measured value of the parameter and D_d is the MCL. The parameters that are within the MCL are assigned a rating score of 100. The water quality parameters along with the rating scale used in M_{ED}-WQI are provided in Table 1.

In case of pH, the activity of proton (H^+) was used for deviation, D_i, calculation. D_i for turbidity, hardness, chloride, fluoride and TDS were calculated using the measured data. In the case of dissolved oxygen, as D_i will be negative as the quality of water deteriorates, modulus of the deviation has been used.

Development of sub-index functions (S_i)

Sub-index functions are formulated as continuous functions for each rating scale. Sets of linear equations were developed for each parameter having varied ranges of deviation. The plots of S_i function are provided in Figs. SI1A and SI1B. The proposed sub-indices functions are given in Table 2.

2.4.3. *Estimation of relative weights*

For calculations of relative weights, a entropy-based approach has been adopted. The concept of entropy method was introduced by Shannon in 1948 (Shannon, 1948) which captures the measure of randomness and disorderliness in the information. Shannon's information theory interprets the importance of relative intensities (weights) of the criterion depending on the dispersion among data (Gorgij et al., 2017). The most significant advantage of the entropy method is that it provides reliable outcome due to the elimination of interference by human factors in the assignment of weights to parameter (Pei-Yue et al., 2010).

In the entropy method, the value of information entropy (e_j) varies from 0 to 1. The degree of randomness is proportional to the degree of dispersion in the measured value. A criterion with a lower information entropy value (e_j) is assigned a higher weight.

To calculate relative weights of water quality data having m number of samples (i = 1,2,3,..,m) and n number of parameters (j = 1,2,3,..,n), the eigenvalue matrix,'X', is arrived as follows (Pei-Yue et al., 2010):

$$X = \begin{pmatrix} x_{11} & x_{12} & . & x_{1n} \\ x_{21} & x_{22} & . & x_{2n} \\ . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mn} \end{pmatrix} \tag{2}$$

where x_{mn} represents the n^{th} parameter value for m^{th} sample. The

Table 3
Proposed M_{ED}-WQI classes for surface water.

S No	M_{ED}-WQI Score	Class	Water Status
1	100	I	Excellent
2	(100,80]	II	Good
3	(80,50]	III	Fair
4	(50,20]	IV	Poor
5	(20,0]	V	Heavily-polluted

Table 4
Comparison of relative weights of various parameters between M_{ED}-WQI and CWQI.

S No	Parameter	M_{ED}-WQI	CWQI
1	pH*	0.3402	0.3111
2	Turbidity	0.1655	0.1070
3	Hardness	0.1522	0.1070
4	TDS	0.1825	0.3111
5	Chloride	0.0975	0.1070
6	Fluoride	0.0621	0.0568

* The weight factor for pH in M_{ED}-WQI was estimated using $[H^+]$ activity (i.e. 10^{-pH}).

normalized matrix,'Y', is given as follows:

$$Y = \begin{pmatrix} y_{11} & y_{12} & . & y_{1n} \\ y_{21} & y_{22} & . & y_{2n} \\ . & . & . & . \\ y_{m1} & y_{m2} & . & y_{mn} \end{pmatrix} \tag{3}$$

The normalization matrix,Y, is formulated wherein,

$$y_{ij} = \frac{x_{ij} - (x_{ij})_{min}}{(x_{ij})_{max} - (x_{ij})_{min}} \tag{4}$$

The parameter index amount (P_{ij}) and information entropy (e_j) are calculated as:

$$P_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}} \tag{5}$$

$$e_j = -K\sum_{i=1}^{m} P_{ij}\ln P_{ij} \tag{6}$$

where K $= 1/\ln(m)$ wherein 'm' denotes the number of samples

After estimating the amount of entropy, the weights of parameters 'w_j' are computed using the following expression (Gorgij et al., 2017):

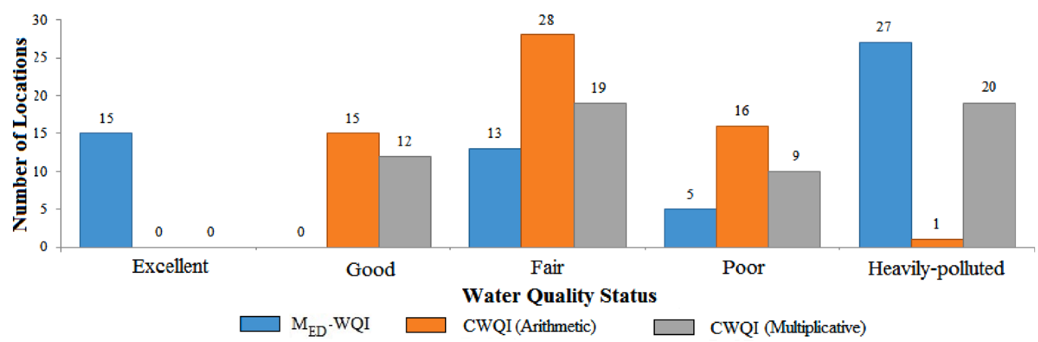

Fig. 3. Comparison of M_{ED}-WQI with CWQI on synthetic dataset.

Table 5
Comparison of relative weights for river Ganga.

S No	Parameter	M_{ED}-WQI	CWQI
1	pH	0.2026	0.3112
2	Hardness	0.0362	0.1069
3	Chloride	0.3051	0.1069
4	Fluoride	0.0486	0.0569
5	TDS	0.1091	0.3112
6	Turbidity	0.2984	0.1069

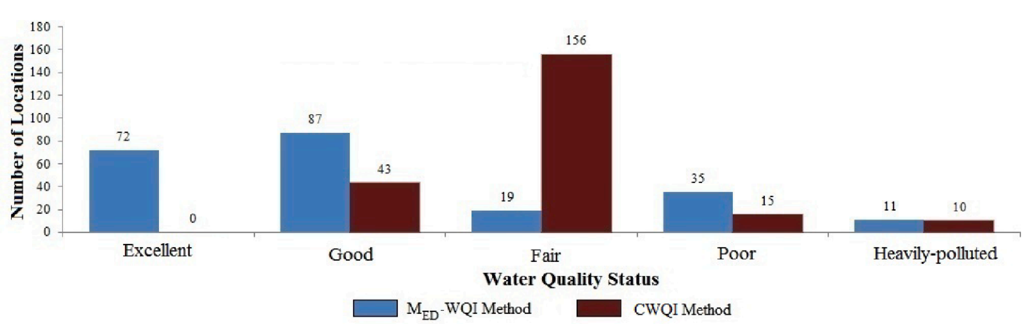

Fig. 4. Comparison of M_{ED}-WQI and CWQI for river Ganga.

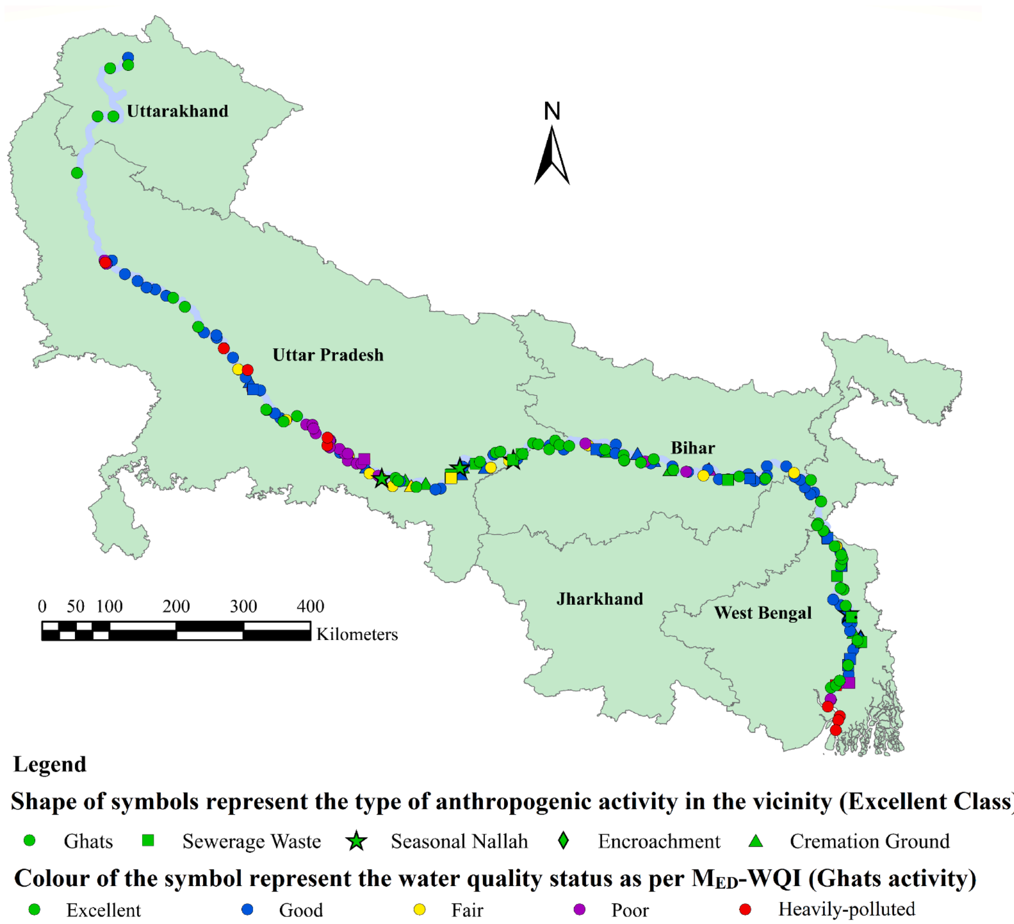

Fig. 5. Water Quality Indices of river Ganga using M_{ED}-WQI.

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n} 1 - e_j} \quad (7)$$

2.4.4. Multiplicative aggregation of sub-indices

For the computation of M_{ED}-WQI, geometric averaging has been chosen as a mode of aggregation which is given as follows (Uddin et al., 2021):

$$M_{ED} - WQI = \prod_{i=1}^{n} S_i^{w_i} \quad (8)$$

where S_i is the sub-index value of i^{th} water quality parameter, w_i is the relative weight of i^{th} parameter and n is the number of parameters. M_{ED}-WQI is divided into five classes for ranking the water quality status. The details of the proposed various quality classes are provide in Table 3.

2.4.5. Visual basic based spreadsheet program for M_{ED}-WQI

In this study, Visual Basic application, available within the Microsoft Excel© 2007 package, has been used for coding the WQI formulations (Panchawan, 2021). For determining WQI, two separate macros were created, viz. one for estimation of relative weights using entropy method and the other for calculation of sub-index functions along with WQI class assignment.

2.5. Comparison of M_{ED}-WQI with CWQI

In this study, the performance of M_{ED}-WQI has been compared with CWQI approach used in Singh et al. (2019). Singh et al. have used arithmetic mode of aggregation with Saaty's AHP method for estimating WQI scores, whereas M_{ED}-WQI uses multiplicative mode of aggregation. To enable a fair comparison, M_{ED}-WQI is compared with both arithmetic and multiplicative aggregation mode of CWQI for synthetic dataset. In the case of river Ganga dataset, M_{ED}-WQI results were compared with CWQI, as proposed by Singh et al. (2019), i.e. arithmetic aggregation mode only. Further in these comparisons the water quality classification as adopted by Singh et al. (2019) has been used (Table SI3A).

3. Results and discussion

3.1. Evaluation of M_{ED}-WQI on synthetic data

The M_{ED}-WQI approach has been evaluated by applying it on a synthetic dataset of 60 samples that contained the following water quality parameters viz. pH, hardness, chloride, fluoride, TDS and turbidity. A comparative analysis of the M_{ED}-WQI vis-a-vis CWQI method adopted by Singh et al. (2019) has been performed. It shall be noted that changes to sub-index function for fluoride, in the range 0–0.7 mg/L, was made before the comparison exercise. The details of this revision has been elaborated in Table SI3. The relative weights of various parameters for M_{ED}-WQI and CWQI are provided in Table 4.

Comparison of relative weights of M_{ED}-WQI with CWQI indicated that in the latter method the subjective assignment of ranks resulted in same relative weights for pH and TDS. Similarly, in the case of hardness, chloride, and turbidity the values of relative weights are the same. On the contrary, entropy approach used in M_{ED}-WQI is devoid of the subjective bias resulting in distinct values of relative weights. Overall, the comparison of CWQI and M_{ED}-WQI shows similar trend in weights with pH having the maximum weight factor and fluoride having the least

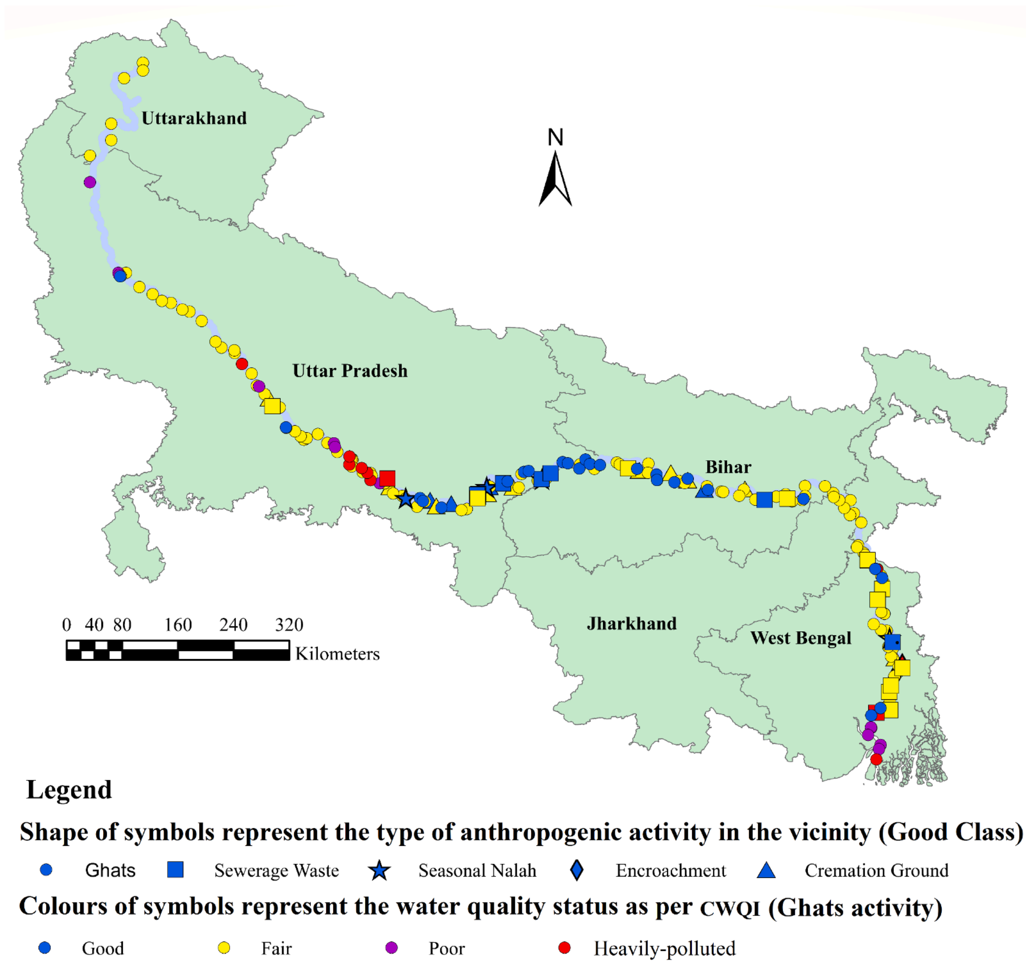

Fig. 6. Water Quality Indices of river Ganga using CWQI.

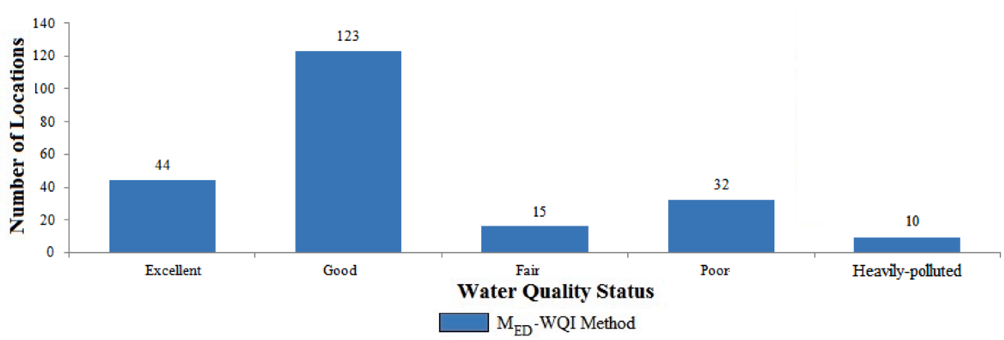

Fig. 7. M_{ED}-WQI of river Ganga (Dissolved Oxygen inclusive).

weight factor.

Though Singh et al. (2019) used CWQI method in arithmetic mode of aggregation, the comparison of M_{ED}-WQI vis-a-vis CWQI has been performed on both arithmetic and multiplicative modes of aggregation (Fig. 3). The results of M_{ED}-WQI indicate that the samples having the parameters within the MCL been classified into excellent class. Whereas, the samples having parameters with highest deviation are classified into heavily-polluted class (Fig. 3). In contrast, CWQI (arithmetic) results in clustering of the data into good and fair classes. Though all parameters are within MCL, none of those are classified into excellent water quality class. Furthermore, the samples with very high deviation in water quality parameters are being mostly classified into poor class and none of the samples fall into heavily-polluted class (Table SI1).

A comparison of arithmetic and multiplicative aggregation mode of Saaty's AHP based CWQI indicates that the latter mode which is based on geometric averaging, is more sensitive to capture the water quality class when few parameter exceeds the MCL. It has been observed that when few parameters exceeded the MCL, those samples are classified into poor and heavily-polluted status in multiplicative aggregation whereas these were entirely classified into fair status in arithmetic aggregation mode (Table SI1).

3.2. M_{ED}-WQI on river Ganga

The proposed M_{ED}-WQI has been applied to assess the water quality of river Ganga that comprised of 7 parameters for 224 locations at

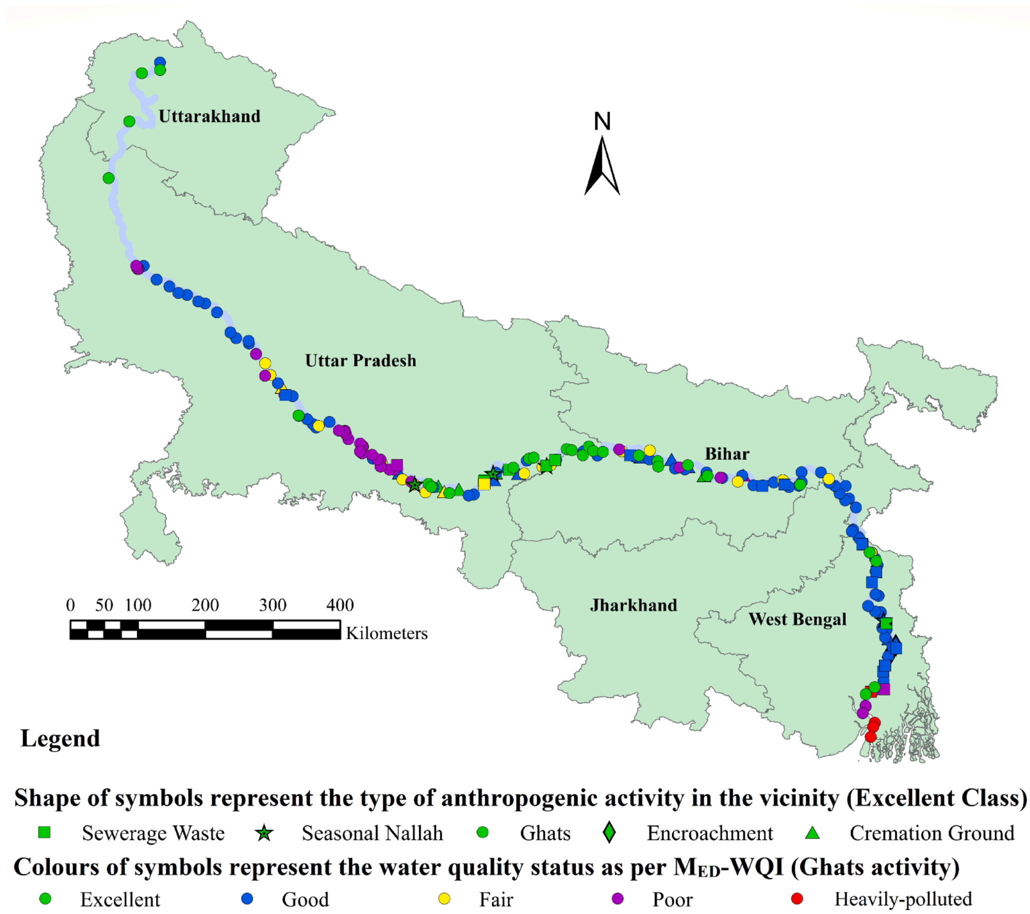

Fig. 8. Water Quality Classes of river Ganga using M_{ED}-WQI (including DO parameter).

various points along the river stretch. CWQI, in arithmetic aggregation mode, as proposed by Singh et al. (2019) has been used for comparison with M_{ED}-WQI. Six water quality parameters viz. pH, hardness, chloride, fluoride, TDS and turbidity were considered in the calculation of WQI by both methods. Though dissolved oxygen data was available, it was not used for WQI calculations as it was not considered in Singh et al. (2019) study and lacks sub-indices functions. The relative weights for both M_{ED}-WQI and CWQI methods are presented in Table 5.

A comparison of relative weights of M_{ED}-WQI with CWQI represents that in the latter method the weights of pH and TDS are the same. Likewise, hardness, chloride, and turbidity have the same relative weights. On the contrary, in M_{ED}-WQI method, the relative weights are distinct representing randomness in the distribution of parameters. Turbidity, one of the important surface water quality parameter, has been assigned significantly higher weight in M_{ED}-WQI in comparison to CWQI (Table 5). The order of weights in M_{ED}-WQI is chloride $\simeq$ turbidity $>$ pH $>$ TDS $>$ fluoride $\simeq$ hardness.

The results of water quality index for river Ganga calculated by both M_{ED}-WQI and CWQI method are presented in Fig. 4. A comparison of M_{ED}-WQI and CWQI shows that in the latter method most of the dataset are primarily classified into fair and good classes whereas in the case of M_{ED}-WQI method the dataset is distributed into excellent, good, fair and poor quality classes. As expected, in M_{ED}-WQI, the samples were categorised into excellent class when all parameters are within MCL indicating it is a more rational approach in representing the water quality class. In Saaty's AHP based CWQI none of the samples are classified into excellent class. Furthermore, the number of samples identified into good and poor classes by CWQI are 43 and 15, respectively, which are significantly lower when compared to M_{ED}-WQI. This clearly indicates that M_{ED}-WQI's deviation-entropy based approach performs better in classifying the water quality data into appropriate classes. Whereas, the CWQI method results in clustering of water quality dataset into only few classes. The map of water quality classes of river Ganga using M_{ED}-WQI is shown in Figs. 5 and 6. The details of the dataset and corresponding water quality class are elaborated in Table SI2.

Furthering the study, M_{ED}-WQI has been applied on river Ganga dataset with seven water quality parameters that included DO and adopting the proposed water quality class(Table 3). DO is one of the most important surface water quality parameter that indicate the level of pollution in the river stretch due to various anthropogenic activities. The sub-index functions for DO is provided in Table 2 and the relative weights obtained for computation of WQI are provided in Table SI4. The results of M_{ED}-WQI for the river Ganga dataset are represented in Fig. 7.

The results depict 10 samples in the heavily-polluted class mainly at 24-Pargana district in West Bengal state and Bijnor, Aligarh and Bulandshaher in the state of Uttar Pradesh. 32 samples were classified into poor class which are located at mainly 22 locations in Uttar Pradesh, 4 locations in Bihar, and 6 locations in West Bengal. 15 samples in the fair class were identified at 8 locations in Uttar Pradesh and 7 locations in Bihar. 123 samples in the good class were identified at 43 locations in Uttar Pradesh, 27 locations in Bihar, 4 locations in Jharkhand, 48 locations in West Bengal and 1 location in Uttarakhand. Further, 44 samples in the excellent class were identified at 25 locations in Uttar Pradesh, 8 locations in Bihar, 6 locations in West Bengal and 5 locations in Uttarakhand (Fig. 8).

The M_{ED}-WQI results shows strong correlation of water quality class with the anthropogenic activities in the vicinity of the sampling site. The M_{ED}-WQI of heavily-polluted and poor classes were associated with maximum anthropogenic activities like sewerage disposal points and industrial pollution. The samples under fair class has been associated with poorly maintained ghats that undergoes disposal of garbage, plastics, dead bodies of animals and exhibits practice of open defecation. Good and excellent water quality classes were associated with sites having evidence of bacteria biophage that aids in self-cleansing of the water (Dimri et al., 2019). Moreover, M_{ED}-WQI in excellent class was observed in many downstream locations that are identified as heavily-polluted class. This may be attributed to the self-cleansing capacity of the river.

The results of this study depict that the water quality of river Ganga in Uttarakhand state is predominately in excellent category due to minimal anthropogenic activities (Kumar et al., 2021). But as we approach major cities of Uttar Pradesh, the water quality shows deterioration especially in towns viz. Bijnor, Raibareli, Kanpur, Prayagraj, and Varanasi. Hence, water quality close to these towns fall into poor or heavily-polluted class which has been reported in earlier studies as well (Maji and Chaudhary, 2019). The correlation between anthropogenic activities like sewerage waste disposal, ghat activities and cremation can be noted in Fig. 8. However, the water quality in Mirzapur, Ghazipur, and Balia district of Uttar Pradesh is under excellent or good category as the anthropogenic activities in this area are significantly less as supported by earlier studies (Singh et al., 2007). In Bihar and Jharkhand, predominantly, the water quality of river Ganga lies in the good class due to less population along the river stream and hence less anthropogenic activities (Pandit et al., 2020). However, in some regions of Chapra, which has marshy land, the quality of water falls into fair or poor class. In West Bengal, the water quality of river Ganga is mainly identified with good class except at the estuary point i.e. Ganga Sagar. The water quality is classified into poor or heavily-polluted class at estuaries due to high salinity and turbidity imparted by coastal processes (Basu et al., 2021).

Overall, the M_{ED}-WQI identified 27.5% of ghats locations into heavily-polluted, poor and fair water quality class whereas 72.5% has been identified in good or excellent water quality classes. 15% of sewerage disposal sites were identified into heavily-polluted, poor, or fair water quality class whereas 85% has been identified in good or excellent water quality class. Similarly for minor activities viz. seasonal nallah, cremation ground, and encroachment 9% of sites were identified into heavily-polluted, poor or fair water quality class whereas 91% has been identified into good or excellent water quality class.

4. Conclusion

In this study, a better approach to capture water quality status using M_{ED}-WQI method has been proposed that could serve as an effective tool for assessing surface water quality. Evaluation of the M_{ED}-WQI in comparison to the existing Saaty's AHP based CWQI method has been demonstrated using a synthetic dataset. The comparison of M_{ED}-WQI with arithmetic and multiplicative aggregation mode of CWQI clearly shows that the data is captured uniformly in M_{ED}-WQI whereas CWQI method resulted in clustering of WQI. Further, CWQI when used in multiplicative aggregation mode significantly distributed the water quality class in comparison to originally proposed arithmetic aggregation mode. Nevertheless, this study indicates M_{ED}-WQI is more effective in water quality class identification when compared to CWQI. Further, M_{ED}-WQI when applied to water quality dataset of river Ganga was able to capture the heavily populated areas along the river and the quality classes correlated well with the type of anthropogenic activities along the river course. In this study, the assessment of water quality status of river Ganga has been done for selected anthropogenic activities only. In future, the study could be expanded for other factors viz. effect of dams, temporal changes in water quality etc. within the proposed M_{ED}-WQI paradigm.

CRediT authorship contribution statement

Mohit Verma: Conceptualization, Methodology, Software, Visualization, Writing - original draft. **Vijay A. Loganathan:** Visualization, Supervision, Validation, Writing - review & editing. **Vinod K. Bhatt:** Investigation.

Declaration of Competing Interest

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Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.ecolind.2022.109319.

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