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Analysis of river water quality in Rourkela Odisha using multiple indices to inform sustainable water management

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The Brahmani River, one of Odisha's major freshwater sources and a vital habitat for native fish species, is facing significant water quality challenges. A study on hydro-chemical characterization of surface water and its suitability for drinking and irrigation purpose was carried out in and Rourkela, an industrial city of Odisha. Over the course of three years (2022 –2025), a total of 12 surface water samples were collected during the pre-monsoon season. This study presents a comprehensive assessment of the river's water quality using multiple Water Quality Indices (WQI), including the British Columbia (BC) WQI, Canadian (C) WQI, Malaysian (M) WQI, Oregon (O) WQI, and Assigned (A) WQI. The pH levels varied from 5.33 to 7.06. This means that the water sample is slightly acidic to alkaline, making it suitable for various types of aquatic life. Analyses across pre-monsoon season reveal that key parameters such as conductivity, hardness, alkalinity, total dissolved solids, Pb^{2+}, Cu^{2+}, and Zn^{2+}, consistently exceed national standards, resulting in water quality ratings ranging from "Poor" to "Very Poor." The deterioration is more pronounced during the tested season, largely due to increased industrial discharge, urban runoff, and lower river flow. Surface water samples in the study area have BCWQI varying from 2 – 95, signifying 20% of water samples as suitable for drinking purpose. Computed CWQI score is estimated as: 27 – 98. Based on the CWQI classification, 40% of the tested specimens contributes fair – poor water quality. The calculated AWQI reading spanned between 36 to 345, indicating 20% of samples are excellent to good water, demonstrating suitable for use for human consumption. MWQI underscored the complex interactions among key pollutants, records a value between 17 and 90, indicating that 60% of samples contribute safe drinking standards. Notably, the OWQI value reports to be a range between 34 to 98. A substantial 20% of samples were classified as exceptional, 20% as good, 20% as fair, while 30% and 10% were grouped under poor and very poor water class. This comparison with case studies from around the world reveals a number of important trends: Agricultural runoff remains a key global source of pollution harming surface water quality; Industrial activities significantly exacerbate pollution, especially in rapidly industrializing nations; Proximity to water bodies is consistently a crucial factor in non-point source pollution impact on surface water; and Urbanization is emerging as an important contributor to non-point source pollution, particularly in developing regions. Hence, these ultimate outcomes align with previous studies on other Odisha rivers, underscoring widespread water quality degradation linked to anthropogenic activities. The results call for urgent action through enhanced pollution control measures, stricter regulatory enforcement, and sustainable management practices to safeguard the Brahmani River's ecological health and the communities depending on it . Aligned with sustainable development goal (SDG) – 6, 11, 12, 13, and 15, these findings construct a solid foundation for well-informed regional policy making and water resource management that aims to reduce pollution from non-point sources and support sustainable surface water quality.

Keywords Brahmani River, Rourkela, Water quality indices, Sustainable development goal, Water resource management, Non-point source

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Water is fundamental to life, supporting a wide array of human activities including irrigation, drinking, sanitation, and industry. Covering nearly 70% of the Earth's surface, water exists in both surface reservoirs such as rivers, lakes and ponds, and underground aquifers[1]. Although groundwater often benefits from natural filtration through soil and rock, leading to lower levels of organic pollution compared to surface water, both sources are increasingly threatened by contamination from various anthropogenic activities. Surface water makes up roughly 0.3% of the world's freshwater resources and is essential for drinking, agriculture, and industrial purposes[2, 3]. In recent decades, river water quality has suffered a significant decline due to a combination of natural processes and human activities, including agricultural runoff, urbanization, and industrial discharges. For communities and ecosystems to survive in arid and semi-arid regions, surface water is the only reliable source of water. Seasonal precipitation further exacerbates pollution through surface runoff, carrying untreated effluents into rivers[4]. However, this critical resource is becoming more and more endangered by contamination, with heavy metal pollution becoming a major worldwide issue[5]. The exposure to heavy metals has significant toxicological effects. Long-term exposure to tainted surface water can have serious negative health impacts, such as carcinogenicity, nephrotoxicity, and neurotoxicity[6]. Copper and Zinc hinder renal and neurological processes, while lead, a known strong carcinogen, has been connected to a number of malignancies[7].

According to the World Health Organization, over 2 billion people worldwide rely on unsafe surface water, with developing countries like India facing particularly acute challenges due to rural populations' dependence on these sources[8]. These hazards are made worse by the bioaccumulation of heavy metals in food chains, which makes pregnant women, children, and other vulnerable groups more susceptible. Growing concerns over water pollution, driven by factors such as climate change, trace element contamination, and nutrient overload[9]. Chronic exposure to these contaminants has been associated with developmental issues, cardiovascular diseases, and premature mortality, making the issue not only an environmental but also a significant public health concern[10]. These contaminants enter water systems via both man-made and natural means. The background levels of these metals are caused by mineral weathering and leaching, but their concentrations are greatly increased by mining operations, industrial effluents, agricultural runoff, and inappropriate waste disposal[11]. Hence, this duality of sources underlines the urgent need for continuous monitoring of river systems to protect both ecosystems and public health. Effective management hinges on clear, reliable assessments of water quality, but the diversity of parameters and methodologies often complicates this task[12].

Water Quality Indices (WQIs) were developed to simplify these complexities, condensing multiple water quality parameters into a single, understandable score, making it an accessible tool for decision-making by policy makers and the public[13, 14]. Traditional WQIs application have been effective in summarizing water quality data but often fall short in providing a detailed understanding of pollution dynamics[15, 16]. Since Horton's pioneering work in 1965, numerous indices have been introduced worldwide, including the National Sanitation Foundation WQI, Weighted Arithmetic WQI (WAWQI), British Columbia WQI (BCWQI), Canadian Council of Ministers of the Environment WQI (CWQI), Assigned WQI (AWQI), Malaysian WQI (MWQI), and Oregon WQI (OWQI)[17, 18, 19]Alobaidy et al., 2010,[20, 21]. These indices are significant because they simplify complex water quality data by aggregating multiple physicochemical and biological parameters into a single, interpretable value. Recent advancements[22] highlighted these tools, which have become essential for policymakers and environmental managers worldwide, facilitating consistent evaluation and comparison of surface water quality[23]. This allows for quick assessment of water suitability for various uses such as drinking, agriculture, recreation, and ecosystem support. The benefits of WQIs lie in their ability to facilitate comparative studies, long-term monitoring, and effective communication to policymakers, researchers, and the general public[24]. As a result, these methods enhance the understanding of pollution dynamics by identifying sources, uncovering trends[25, 26], and interpreting relationships among water quality parameters. Each index reflects a unique methodological approach, often incorporating weighting factors, parameter-specific sub-indices, and guideline thresholds, ensuring flexibility across regions[27]. Their growing use emphasizes the importance of standardized, science-based tools in global water resource management. By integrating multipath risk modelling with sensitivity analysis, the research provides a thorough method for comprehending health hazards in urban-industrial settings, supporting the creation of focused surface water management plans for South India's rapidly urbanizing regions[28].

India, a nation intricately tied to its rivers, relies heavily on these water bodies for livelihood, agriculture, and ecosystem and environmental health. Among these, the Brahmani River, flowing through Rourkela City, holds unique ecological and socioeconomic importance since it is popularly known as steel city of Odisha, has several green spaces in the form of parks such as Indira Gandhi Park sector – 4, Nehru Park in front of ISPAT General Hospital, Udit Nagar Park, Children Park at Chhend, and Sona Udyan Fertilizer[29, 30]. Surface water is essential to these green areas' sustainability. With a 20% decadal population growth rate, Rourkela city is growing in a variety of ways. Without much control or treatment, waste water from electroplating facilities, tanneries, and residential sources leaks into waterways[31]. The watershed is an important but little-studied region for examining the dynamics of non-point source pollution because of the combination of poorly managed industrial expansion, inadequate sewage infrastructure, and land use change[32, 33]. However, the river is increasingly threatened by erosion, climate change, and pollution, which compromise its ecological functions and the well-being of communities dependent on it. The problem of heavy metal contamination in surface water is mostly caused by the hydrogeological and environmental characteristics of Rourkela. Due to its heavy reliance on surface water for agricultural and residential use, the area is susceptible to contamination from both natural and man-made sources[34]. Iron, and Copper were chosen for examination since they have a geogenic origin and are frequently discharged into surface water as a result of rocks and soil minerals weathering naturally, a process that is distinctly typical of lithological formations. In contrast, Lead and Zinc were selected due to their high toxicity, environmental persistence, and close linkages to human activities such agricultural runoff, incorrect waste management, and industrial discharges[35, 36]. The exploitation of surface water has caused the water table to drop and the quality of the water to deteriorate. Surface water quality declined as a result of the monsoon pattern's aberration and the rise in impermeable urban coverings. Therefore, surface water quality is crucial for the growth and maintenance of green spaces in a city[37]. While global studies have demonstrated the value of integrating WQI with advanced indices, such applications remain underutilized in India, particularly for urban cities like the Rourkela. Most existing studies have focused narrowly on physicochemical analyses without leveraging advanced techniques to uncover deeper insights into pollution sources and trends. Specifically, limited efforts have been made to apply these integrated approaches to the Brahmani River, underscoring a critical knowledge gap in the field.

By doing a comprehensive assessment of the city's water quality using five internationally accepted indices—the BCWQI, CWQI, AWQI, MWQI, and OWQI—this study seeks to close this crucial gap by identifying the main sources of contamination and evaluating drinking water quality standards. Systematic sampling across multiple locations along the river ensures the representatives of the data, while comparison of various studies allow a deeper interpretation of water quality dynamics. The use of radar diagrams enables high resolution mapping of contamination trends. By applying multiple indices concurrently, this research not only provides a robust characterization of the river's health but also examines the consistency and comparative reliability of different WQIs in a regional context. The findings may help for targeted management strategies to preserve the Brahmani River's ecological integrity and safeguard the associated communities. The resulting results could offer practical advice for managing water resources sustainably and support international initiatives towards sustainable development goals – SDG 6: (Clean Water and Sanitation), SDG 11: (Sustainable Cities and Communities), SDG 12: (Responsible Consumption and Production), SDG 13: (Climate Action), and SDG 15: (Life on Land). This study aids in the development of practical plans for accomplishing the SDGs and guaranteeing a sustainable future by clarifying the intricate connection between industrial operations, surface water quality, and Non-Point Source (NPS) pollution.

Materials and methods

Overview of the study area

The Brahmani River system is one of the country's major river networks. The region surrounding Rourkela city, a significant industrial complex, hosts a large steel plant alongside numerous medium and large-scale industries, contributing substantially to the area's industrial activity[38]. The population density of Rourkela urban area is about 6696 persons per km^2 approximately. Rourkela, located in the Sundergarh district of Odisha, India, lies at an elevation of 219 meters above sea level, positioned at approximately 22.12°N latitude and 84.54°E longitude. The location map adopted in this study is illustrated in Figure 1. The Koel River runs westward to the north of Rourkela before joining the eastward-flowing Sankh River near Vedavyas. The united river below this confluence is known as the Brahmani, and it runs south through the region. Rourkela, an important industrial city, spans an area of 264.7 km^2 and is home to a population of over 400,000 people[30]. Iron ore, dolomite, and coal belts around the region. The Durgapur hill range divides the city into two parts: northern and southern clusters. In the region, air temperatures drop to as low as 6 °C during winter (December–January) and can rise to 47 °C in summer (May). Average relative humidity ranges between 35% and 85%, with the highest humidity typically occurring in July. With the monsoon period accounting for greater than 70% of the total annual rainfall, the average annual rainfall amounts to 137 cm[33]. The region exhibits a diverse land use and land cover pattern, ranging from rural areas at one extreme to urban zones at the other. Between these two extremes lies an extensive geographical

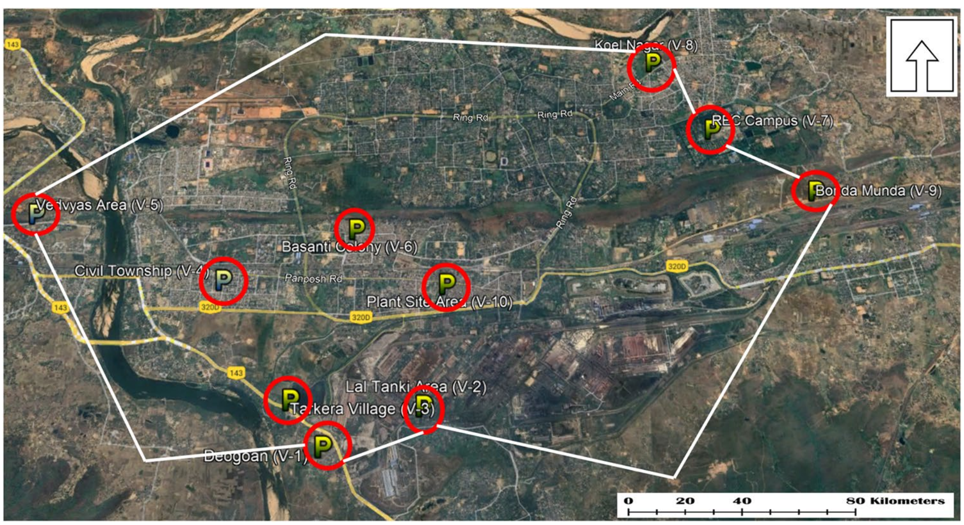

Fig. 1. Study area map and locating the sampling sites on the Rourkela City, Odisha. This figure was prepared using Arc GIS Desktop 10.5. The shapefile used in the figure were extracted from the Survey of India (https://www.surveyofindia.gov.in/) and is alternatively used for delineating administrative boundaries, and other geographical features relevant to the study.

area with varying degrees of development and land utilization[34]. The distinct classifications of "rural and urban" environments are frequently muddled in this sector, and such areas are referred to as "rurban settings". However, urban, rurban, and rural settings are unified systems in which people, ideas, and materials exchange[36]. The congestion in all these areas urges green spaces in order to reduce pollution in the environment.

Water sampling and collection

A total of 12 water samples were collected from different locations across Rourkela during the pre-monsoon season (March–May) and detected over a three-year period from 2022 to 2025. The analysis was focused on the pre-monsoon season because this period reflects the most critical water-quality conditions, when river flows are lowest and pollutant concentrations are typically highest. These factors make the pre-monsoon season ideal for identifying dominant contamination sources and assessing worst-case scenarios without interference from monsoon-induced dilution or fluctuating runoff. Moreover, focusing on the pre-monsoon season helps isolate water-quality variations without the confounding effects of heavy rainfall, increased runoff, or sudden inflows that occur during the monsoon. Limiting the study to this season also provides a stable dataset for isolating anthropogenic influences. The sampling stations were strategically chosen based on two primary criteria: first, their proximity to key industrial areas, including the mega steel plant and other medium to large-scale industries[39], to assess the impact of industrial effluents on water quality; and second, their representation of different land use zones, ranging from urbanized sectors to more rural and less disturbed areas, to capture spatial variability within the river system[40]. The samples were analysed for pH, electrical conductivity (EC), total dissolved solids (TDS), total hardness (TH), alkalinity, major cations such as sodium (Na^+), iron (Fe^{2+}), copper (Cu^{2+}), zinc (Zn^{2+}), lead (Pb^{2+}) and potassium (K^+), and anions as: phosphate (PO_4^{3-}), by adopting standard analytical procedures[41]. The selection of water quality parameters was guided by their relevance to both environmental health and human usage[42]. Surface water samples were collected in 1.5-liter plastic bottles equipped with stoppers. Prior to sampling, each bottle was thoroughly cleaned with 2% nitric acid and rinsed three times with distilled water, then stored in a clean environment. During sampling, bottles were filled completely to eliminate air space and securely sealed to prevent leakage. Each container was clearly labelled with the sampling location and date[37].

The water samples were tested for various parameters in the laboratory of C.V. Raman Global University laboratory, and verified from State Pollution Control Board, Odisha. Temperature, Electrical conductivity (EC), and pH were measured using digital meters immediately after sampling. Alkalinity is typically measured using titration. The most common method is acid-base titration, where a known concentration of acid (usually sulfuric or hydrochloric acid) is added to a water sample until a specific pH endpoint (usually around pH 4.5) is reached, indicating the neutralization of alkaline substances[43]. Flame photometer was used to measure Na^+, Cu^{2+}, Zn^{2+}, Pb^{2+}, Fe^{2+}, and K^+ ions. Heavy metals like copper (Cu^{2+}), zinc (Zn^{2+}), lead (Pb^{2+}), and iron (Fe^{2+}) were examined due to their potential toxicity and prevalence in industrial discharges. Heavy metals measurements were verified through standard calibration and routine quality control procedures. Instrument calibration was performed using certified multi-element standard solutions covering the expected concentration ranges. Calibration curves were generated for each metal, and only those with acceptable correlation coefficients (typically $R^2 \geq 0.99$) were used. Additionally, nutrients like phosphate (PO_4^{3-}) and ions such as sodium (Na^+) and potassium (K^+) were monitored to assess the effects of agricultural runoff and urban waste on the aquatic ecosystem. TDS is estimated by volumetric titrations, whereas PO_4^{3-} were determined by spectrophotometric techniques. This comprehensive parameter selection ensured a holistic assessment of water quality, addressing both natural background conditions and anthropogenic influences[44].

To verify the accuracy of all chemical analyses, the Ion Charge Balance Equation, and Ion Balance Error Computation methods, as outlined by [31] and presented in Equation (1), were employed. These methods assessed the balance between total cations (Na^+, K^+, Cu^{2+}, Zn^{2+}, Pb^{2+}, Fe^{2+}) and the total anion (PO_4^{3-}) in each surface water sample, and computed the percentage error (Z) using the following equation:

$$Z = \left\{ \sum \text{Cations (U)} - \text{Anions (H)} / \sum \text{Cations (U)} + \text{Anions (H)} \right\} * 100 \tag{1}$$

Where, the sum of major cations and anions are expressed in mg/L. The reaction error for all surface water samples was within the acceptable limit of ±6%, thereby confirming the precision and reliability of the analytical data.

Methods for assessing water quality indices

A well-known indicator for assessing surface and groundwater quality, the water quality indexing technique assists in providing the public and policymakers with data on water quality[45]. The index is believed to be the best suitable for assessing how trash disposal affects adjacent surface and groundwater sources[16]. In recent years, numerous countries and scholars have produced a number of WQIs to comprehend the criteria of surface and groundwater for diverse uses, including as drinking and agricultural[18]. Some notable ones include the following: the British Columbia Water Quality Index (BCWQI) developed by[46], the Canadian Council of Ministers of the Environment Water Quality Index (CWQI) developed by[47], the Assigned Water Quality Index (AWQI) developed by[48], the Malaysian Water Quality Index (MWQI) developed by[49], and the Oregon Water Quality Index (OWQI) developed by[50]. The methodology of the various WQIs is explained below.

British Columbia Water Quality Index (BCWQI)

The concept of BCWQI was developed in 1995 by the British Columbia Ministry of Environment following a comprehensive review of more than a hundred water bodies across the province[46]. The purpose of the BCWQI was to provide a standardized, quantitative method for summarizing complex water quality data into a single, interpretable value that could support water resource management and communication with policymakers and the public[17, 51]. The mechanism enumerate functions by comparing measured water quality parameters against predefined objectives or guideline values. The index incorporates three key factors: scope (the number of variables that exceed objectives), frequency (how often the objectives are not met), and amplitude (how much the objectives are exceeded). One of the primary benefits of the BCWQI is its ability to simplify complex water quality data without losing essential scientific meaning. This simplification allows water quality trends to be tracked over time, compared across sites, and effectively communicated to non-technical stakeholders[52]. The significance lies in its versatility and applicability across a variety of aquatic environments—rivers, lakes, and estuaries. It also supports ecosystem-based water management by considering multiple parameters related to drinking, recreational, and aquatic life standards[53]. Here we calculate the BCWQI using 12 parameters. Following is the BCWQI equation (2)' which is derived from the work of[54].

$$\mathrm{BCWQI} = \sqrt{\frac{\mathrm{H}_1^2 + \mathrm{H}_2^2 + (\frac{\mathrm{H}_3}{3})2}{1.453}} \tag{2}$$

Where H_1 is the overall number of unmet objectives (as a percentage of all objectives checked), H_2 is the frequency of unmet objectives (as a percentage of all instances of objectives checked), and H_3 is the maximum variation (as a percentage) for any given objective. For BCWQI, the possible values are 0 to 100. If the value is near 0, then the water is of high quality. Extremely low water quality is indicated by values near 100. Excellent (0–3), good (4–17), fair (18–43), borderline (44–59), and poor (60–100) are the five places the outcomes can be pushed[55].

Canadian Water Quality Index (CWQI)

In the year 2001, the Canadian government created the CWQI, drawing inspiration from[56] and BCWQI[18]. A key benefit of the CWQI is its ability to generate a single, easy-to-understand score, which supports informed decision-making, public communication, and environmental reporting[57]. It enables inter-regional comparisons and long-term monitoring, making it a valuable tool for water resource managers, researchers, and policymakers[20]. Its flexible design also allows adaptation to different water uses, such as drinking, aquatic life, irrigation, or recreation. In this case, the CWQI is computed using twelve parameters such as pH, EC, TDS, alkalinity, TH, Cu^{2+}, Zn^{2+}, Pb^{2+}, Fe^{2+}, Na^{+}, K^{+}, and PO_4^{3-}. Its significance lies in offering a standardized national framework for evaluating and communicating water quality conditions across diverse aquatic systems in Canada. The following is the CWQI formulation according to[58].

F_1 (scope measure) represents the proportion of parameters (out of the total number of parameters tested) that fail to meet the criterion at least once within the specified time period[59]. The equation (3) is used for calculation.

$$\mathrm{F}_1 = \left(\frac{\text{Number of failed parameters}}{\text{Total number of parameters}}\right) \times 100 \tag{3}$$

F_2, which is a measure of frequency, represents the proportion of tests that do not fulfil the established standards. The factor is computed using the following Eq. (4).

$$\mathrm{F}_2 = \left(\frac{\text{Number of failed tests}}{\text{Total numbre of tests}}\right) \times 100 \tag{4}$$

F_3 (amplitude measure) is computed in three stages and shows the extent to which test findings differ from the standard standards.

(a) An "excursion" refers to the frequency with which a particular concentration exceeds (or falls below, if the guideline is a minimum) the recommended limit. When the measured value is unable to exceed the threshold, the Eq. (5) is used:

$$\mathrm{excursion_i} = \left(\frac{\text{Failed Test Value}_\mathrm{i}}{\text{Objective}_\mathrm{j}}\right) - 1 \tag{5}$$

When the test value must always be equal to or over the threshold, the eq. (6) is implemented to compute the score:

$$\mathrm{excursion_i} = \left(\frac{\text{Objective}_\mathrm{j}}{\text{Failed Test Value}_\mathrm{i}}\right) - 1 \tag{6}$$

(b) The aggregate deviation from standards and values is calculated[60], by summing all the deviations of all the tests and then dividing by the total number of tests (including both those that comply with recommendations and those that do not comply with guidelines). The formula in Eq. (7) provided is utilized to compute the normalized sum of excursions (NSE) parameter:

$$\mathrm{NSE} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{excursion_i}}{\text{Total number of tests}} \tag{7}$$

(c) F_3 is determined in Eq. (8), by applying an asymptotic function to the normalized sum of the excursions from recommendations (NSE), which is then adjusted to fall within the range of 0 to 100[61].

$$F_3 = \left(\frac{\mathrm{NSE}}{0.01 \times \mathrm{nse} + 0.01}\right) \tag{8}$$

The index can be calculated by adding the three elements as vectors and applying Pythagoras' theorem. The sum of the squares of the factors is equal to the square of the CCME WQI. This approach considers the index as a three-dimensional space, where each factor is represented by an axis[62]. The index represented in Eq. (9)' has a direct correlation with all three components in this model[63].

$$\mathrm{CWQI} = 100 - \left(\frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732}\right) \tag{9}$$

The findings are normalized to a range between 0 and 100 using the divisor 1.732. Here, 0 represents "bad or poor" water quality and 100 represents "highest or excellent" water quality. The assessment results can be subdivided into the following five categories: Excellent: 95–100; Good: 80–95; Fair: 65–79; Marginal: 45–64; and Poor: 0–44[64].

Assigned Water Quality Index (AWQI)
The AWQI is a water assessment tool developed by utilizing the standard water criterion and is based on the value of different water characteristics that are meant for usage, such as drinking, irrigation, aquatic life, or industrial processes[65]. A key benefit is its flexibility and adaptability, enabling it to provide accurate and meaningful assessments across various ecological and socio-economic contexts[66]. The core aspect is its ability to translate complex, multi-parameter water data into a single, understandable score, facilitating effective water resource management, monitoring, and policy-making. An evaluation of the AWQI is carried out in this work using 12 parameters: pH, EC, TDS, alkalinity, TH, Cu^{2+}, Zn^{2+}, Pb^{2+}, Fe^{2+}, Na^{+}, K^{+}, and PO_4^{3-}. The significance of this model lies in its customized approach, allowing water quality evaluation to be tailored to the specific requirements of different water uses[21]. This makes it highly relevant for diverse environmental and public health applications. Here is how the AWQI is calculated:

(a) First, a weight (G_i) ranging from 1 to 5 from the[23] study is assigned to each parameter. The standard criteria were obtained together with the mean weight values. The weight with the greatest relative importance was 5 and the weight with the least importance was 1.

(b) In this stage, the relative weight (RW or D) is determined by dividing the sum of given weights by the assigned weight, using the following equation (10):

$$D = \left(\frac{G_i}{\sum_{i=1}^{n} G_i}\right) \tag{10}$$

Where D is the relative weight, G is the assigned weight, and n is the total amount of parameters.

(c) This step shown in Eq. (11), assigns a quality rating scale (T_i) by dividing all the parameters by their normal acceptable criteria, except for pH and DO.

$$T_i = \left(\frac{W_i}{P_i}\right) \times 100 \tag{11}$$

The following equation (12) is used to determine ($T_{pH, DO}$) for pH and DO:

$$T_{pH,DO} = \left(\frac{W_i - V_i}{P_i - V_i}\right) \times 100 \tag{12}$$

Where, W_i stands for calculating water quality parameters, P_i for standard permissible criteria for water quality parameters, and T_i stands for quality rating. The optimal value, V_i, is determined by taking pH to be 7 and DO to be 14.6. When there are no pollutants in the water, $T_i = 0$ and when the quantity of pollutants is equal to the standard acceptable value, $T_i = 100$ are the conditions that are applied in T_i and $T_{pH', DO}$. Therefore, the water is more contaminated the higher the T_i value[24].

(d) The sub-indices (K_i) for each parameter are calculated in the last phase. The WQI is determined by summing up the total K_i. The equations 13 and 14, for calculating the WQI are as follows:

$$K_i = D \times T_i \tag{13}$$

$$\mathrm{WQI} = \sum_{i=1}^{n} K_i \tag{14}$$

The computed WQI values could be classified as < 50 = Excellent; 50 - 100 = Good; 100 - 200 = Poor; 200 - 300 = Very poor; > 300 = Unsuitable[67].

Malaysian Water Quality Index (MWQI)

In 1997, the Malaysian Department of Environment (DOE) developed a comprehensive Water Quality Index (WQI) to evaluate and classify the status of water bodies across the country. As highlighted by Arman et al.[27], this index has since been instrumental in water quality monitoring, environmental reporting, and policymaking. This index is based on 12 specific factors that measure water quality: pH, EC, TDS, alkalinity, TH, Cu^{2+}, Zn^{2+}, Pb^{2+}, Fe^{2+}, Na^{+}, K^{+}, and PO_4^{3-}. These parameters were selected due to their relevance in assessing both drinking and irrigation water quality, especially in areas impacted by industrialization, agriculture, and urban runoff. The study utilizes all 12 characteristics to ascertain the value of WQI. Following the[68] guidelines will help you find the best-fit equation for determining the different sub-indexes. This method involves calculating each sub-index based on the deviation of the measured concentration from its respective guideline or permissible limit, assigning appropriate weights, and aggregating them to obtain the final WQI score. This approach ensures that each parameter's impact on overall water quality is reflected proportionally, based on its significance to human and environmental health[69]. The MWQI has a scale that goes from 0 to 100. Values close to 0 mean that the water quality is very bad. Values close to 100 means that the water condition is very good. The scores can be put into five groups: very poor (0–25), poor (26–50), fair (51–70), good (71–80), and excellent (81–100)[28]. As a result, by incorporating a broader range of parameters, this extended WQI model enhances the sensitivity and precision of water quality evaluations. It is especially useful for site-specific investigations and long-term monitoring in regions experiencing complex water pollution scenarios[13].

Oregon Water Quality Index (OWQI)

In the 1970s, the OWQI was created by the Oregon Department of Environmental Quality to evaluate emerging patterns in water quality across many categories[70]. Water quality status assessment reports were legally obliged to use it. It was based on the Water Quality Index (WQI) developed by the National Sanitation Foundation and selected properties of water using the Delphi Technique (NSFWQI). A key benefit of this approach, is its ability to condense complex, multi-parameter water data into a single, comprehensible score, which enhances the accessibility of scientific information for policymakers, stakeholders, and the general public[71]. It supports long-term trend analysis, helping authorities identify emerging water quality issues and prioritize areas for intervention. In order to classify the water quality factors, we looked at oxygen depletion, eutrophication, dissolved compounds, and health hazards. A weighted harmonic squared mean formula, which is the end product of combining NSFWQI and WAWQI, is what gives rise to the OWQI. This makes it a robust and reliable tool for evaluating the ecological and public health implications of water quality changes. As an upgrade from NSFWQI and WAWQI, the formula has been proposed by[48]. Following Cude's description[72], the equation (15) is presented below:

$$\mathrm{OWQI} = \sqrt{\frac{n}{\sum_{i=1}^{n}\frac{1}{{Sl_i}^2}}} \tag{15}$$

Where SI is the subindex 'i' of various parameters and 'n' signified as total number of subindices. There is a scale from 0 to 100 for the OWQI. Extremely low water quality is indicated by values near zero. Water quality is considered excellent, when the value is close to 100. Very poor (0–59), poor (60–79), fair (80–84), good (85-89), and exceptional (90–100) are the five possible rankings for the outcomes[73],[74].

Results and discussion

As part of the surface water quality assessment in Rourkela City, twelve key physicochemical parameters were analysed to evaluate the condition and potential usability of local water bodies. These parameters included Alkalinity, Potassium (K^+), Sodium (Na^+), Phosphate (PO_4^{3-}), Total Dissolved Solids (TDS), Electrical Conductivity (EC), pH, Copper (Cu^{2+}), Zinc (Zn^{2+}), Lead (Pb^{2+}), Iron (Fe^{2+}), and Total Hardness (TH). The measured concentrations of these indicators were used to determine the extent of natural and anthropogenic influence on water quality[75]. To effectively visualize and compare the variation across sampling sites, the calculated values were illustrated through radar diagrams (Figure 2a-l), providing a multi-dimensional representation of the water quality profile.

Characterization of the surface water chemistry

Temperature stability plays a role in regulating biochemical reactions, microbial activity, and solubility of minerals, and its range is consistent with other tropical aquifer studies[76]. The current observation depicts a recorded study's temperature as: 27.05 - 30 ° C, signifying a normal temperature variation, which is accounted for limited thermal stratification and indicates that the sampled water bodies are predominantly shallow and well-mixed, allowing for rapid thermal equilibration with the surrounding environment[42]. pH is an important parameter for assessing the acidity or alkalinity of groundwater, as it influences the chemical form and mobility of dissolved substances. Computed pH for the tested water samples spanned between 5.33 and 7.06. The study's pH renders slightly acidic nature (average pH = 6.07). This acidity may be attributed to the elevated iron content, which can occur through oxidation and hydrolysis reactions that release hydrogen ions into the water[77]. EC is widely used to estimate the presence of total dissolved solids (TDS) and infer the level of pollutants or mineralization in water bodies[78]. The reported EC value for the surface water specimens varied as: 91 to 854 µS/cm µS/cm, culminates an average score of 539.20, surpassing the WHO threshold of 100 µS/cm. At all water locations, mostly 90%, such high values can often be attributed to anthropogenic factors, including sewage effluent discharge. TDS represents the combined content of inorganic salts and small amounts of organic matter dissolved in water, primarily including minerals such as Ca^{2+}, Mg^{2+}, Na^{+}, K^{+}, HCO_3^{-}, Cl^{-}, and SO_4^{2-}[79]. Observed TDS concentration spanned as 90 to 488 mg/L.

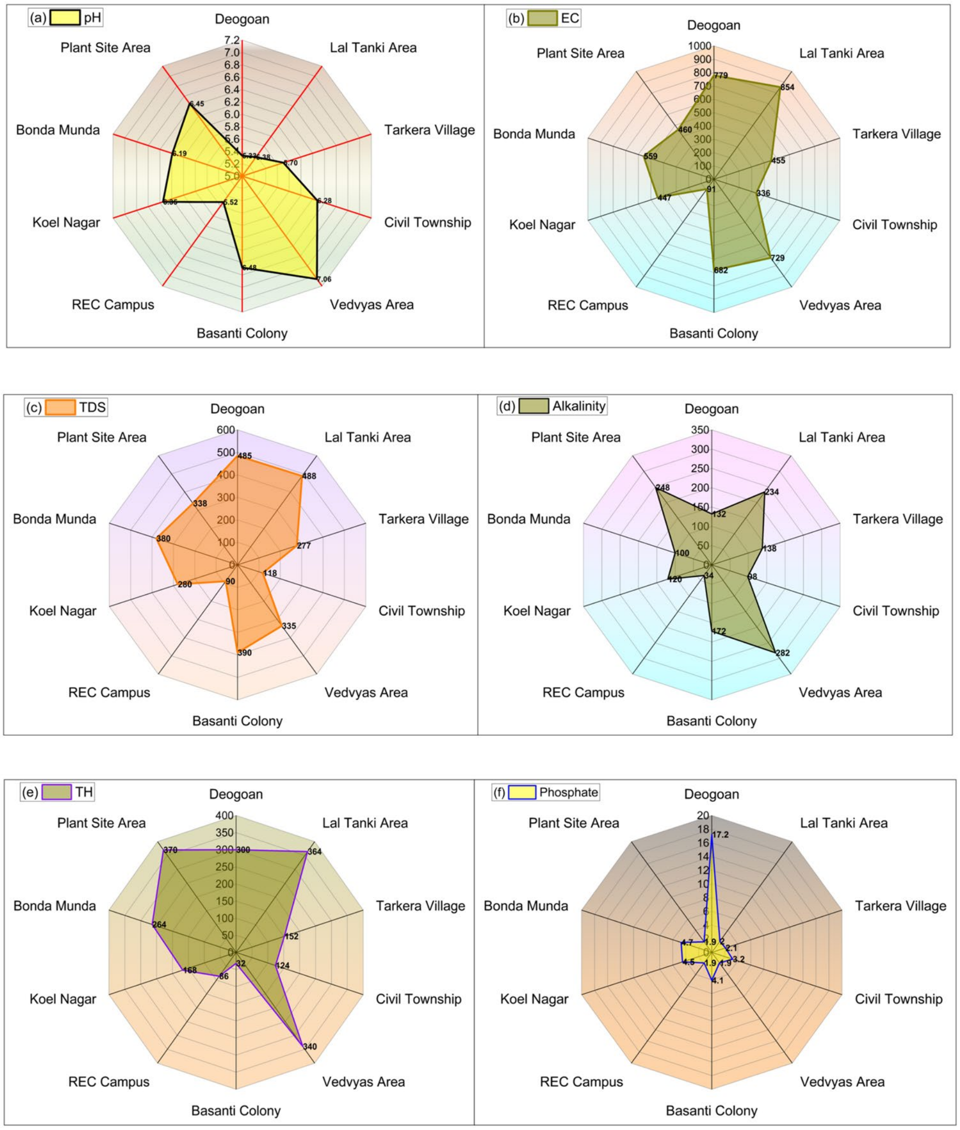

Fig. 2. Water quality variation of measurement parameters: (**a**) pH, (**b**) EC, (**c**) TDS, (**d**) Alkalinity, (e) TH, (**f**) PO_4^{3-}, (**g**) Na^+, (**h**) K^+, (**i**) Pb^{2+}, (**j**) Cu^{2+}, (**K**) Zn^{2+}, and (**l**) Fe^{2+}.

The highest TDS value, 488 mg/L, was observed at P – (2), possibly due to industrial effluents, urban runoff, or natural weathering of minerals in the catchment area[42]. According to WHO water quality guidelines, the recommended alkalinity level for drinking water should generally remain below 100 mg/L. Range of alkalinity content in the examined sampling sites defined in a range: 34 – 282 mg/L. Elevated alkalinity levels (> 100) at V – (1-3), (5-6), (8), and (10), may reflect underlying hydrogeochemical processes, such as carbonate rock weathering, or pollutant loadings contributing to higher concentrations of bicarbonates[80]. For the assessment of TH, the calculated readings for the water samples spanned as 32 - 370 mg/L. Samples from V – (1) and V – (9) exhibited hardness levels just below 300 mg/L, categorizing them as hard water. These primary cause of the contaminant, that have the potential to leach into surface water bodies, increasing the concentrations of calcium and magnesium, and exacerbating hardness levels.[81,82] As per observation, lowest PO_4^{3-} concentration of around 1.9 mg/L, was recorded at sampling point P – (5), suggesting limited anthropogenic influence and relatively clean water conditions[42]. Throughout this study, the PO_4^{3-} concentrations fluctuated between 1.9 and 17.2 mg/L. The permissible level is around 5 mg/L, as addressed by WHO. Subsequently, high phosphate levels at V – (1), is often a sign of anthropogenic pollution, commonly resulting from agricultural runoff (fertilizers), domestic sewage, industrial effluents, and solid waste disposal. Water containing excessive concentrations of sodium (Na^+) is often unsuitable for irrigation purposes, as it can negatively impact soil structure, reduce permeability, and promote alkalinity, ultimately degrading soil fertility, and crop productivity[83]. The Na^+ ion is the most abundant cation, with concentrations fluctuated between 0.10 to 66 mg/L. Relying on output, all tested sites were within the drinking water standards (< 100 mg/L). Computed K^+ concentration varied from 0.1 to 6.0 mg/L. The relatively low concentration across most of the sites can be attributed to the slow weathering of K^+-feldspar minerals and fixation of K^+ ions by clay minerals, which limits its mobility in aquatic environments[84]. On the basis of

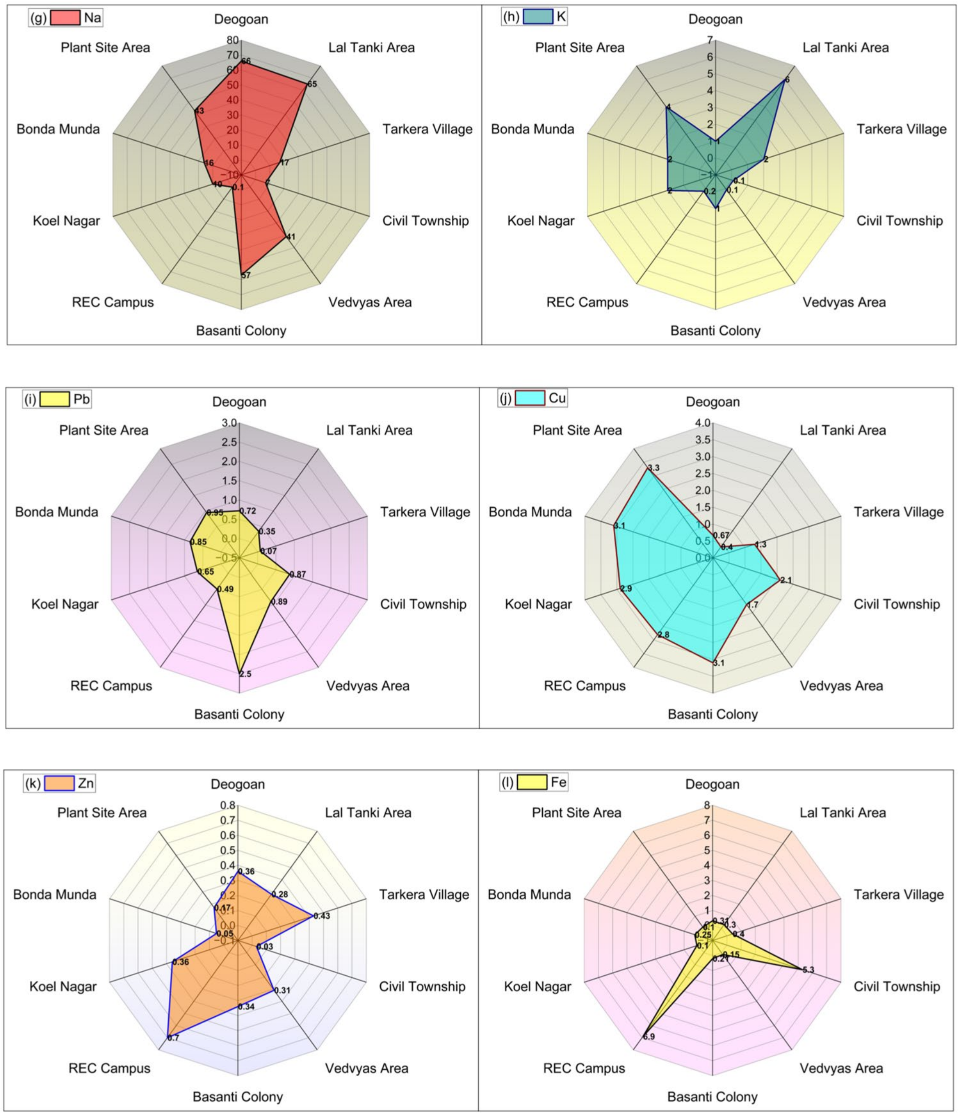

Fig. 2. (continued)

WHO recommendation (< 10 mg/L), the obtained results reveal that almost all surface water specimens were appropriate for drinking and agriculture. Permissible standard of lead (Pb^{2+}) as per WHO criteria is around 0.01 mg/L[42]. Reported lead (Pb^{2+}) content of the water samples in the current investigation ranged as 0.07 to 2.5 mg/L. It is noticed that elevated concentrations at all locations are likely the result of leaching from nearby industrial waste disposal sites, particularly associated with the Rourkela Steel Plant, as well as municipal solid waste dumped in proximity to the water bodies[85]. The present investigation supports copper (Cu^{2+}) value, varied between 0.4 and 3.30 mg/L. The WHO – recommendation for Cu is 0.5 mg/L. Approximately, 90% of locations surpassed the desirable level. This trend in dataset may be influenced by the downstream flow of the Brahmani River, which moves southeast from the Angul district, potentially transporting metal-rich sediments and industrial discharges along its course. Reported Zn^{2+} concentration is found as 0.03 – 0.7 mg/L. Highest value of Zinc (Zn^{2+}) is recorded at V – (7) site. The elevated levels of Zn^{2+} in the study area may be attributed to the geological characteristics, particularly the presence of Lower Gondwana rock formations, also known as the Barakar Formation, which is rich in coal-bearing sedimentary and metamorphic rocks[86]. However, nine of the total samples collected, has surpassed the limiting values. The study's Fe^{2+} content fluctuated as 0.10 – 6.9, indicating a mean of 1.40 mg/L. Approximately, 40% of the total surface water samples recorded concentrations exceeding the recommended limit of 0.3 mg/L[42] for iron (Fe^{2+}) in drinking water[87]. However, increased alkalinity at one location i.e., V – (3), may have enhanced the dissolution of iron - bearing minerals, contributing to higher iron concentrations in the water column[88].

Based on the physicochemical results, the above discussion reflects that Na^{+} and alkalinity exhibited the main ionic dominance in the examined surface water samples. The elevated sodium (Na^{+}) concentrations are indicative of the weathering of silicate minerals, such as feldspars, commonly present in the Precambrian crystalline rocks of the region[89]. The concentrations of trace elements occurred in the following sequence: Cu^{2+}

> Pb^{2+} > Zn^{2+} > Fe^{2+}. The presence of trace metals in surface water can arise from both natural sources (such as rock weathering and soil leaching) and anthropogenic inputs, including industrial discharges, agricultural runoff, and improper waste disposal[90].

A singular or simplistic conclusion derived from the analysis of physicochemical water quality parameters is inadequate, as water quality is governed by numerous interrelated factors that exhibit spatial and temporal variability[91,92]. Relying solely on such an approach may lead to the oversight of complex interactions and synergistic effects among the various parameters, thereby limiting the accuracy and reliability of the overall assessment. Hence, the adopted methods (BCWQI, CWQI, AWQI, MWQI, and OWQI) together provide a more comprehensive, objective, and scientifically robust evaluation. Different analysed parameters and calculated indices values are given in Table 1, and discussed in the following methods.

Quality assessment utilizing BCWQI

The BCWQI is a technique for quickly assessing the quality of a rivers or watershed management method. By giving each piece of complex environmental information to a well-classified value, it seeks to make it easier to understand[93]. BCWQI has a value between 0 and 100. The results were classified into five categories based on their scores (Table 1): excellent (0–3), good (4–17), fair (18–43), borderline (44–59), and poor (60–100). However, Excellent water quality is indicated by values that are near 0. Deficient water quality is indicated by values near 100. Figure 3a gives a detailed example of how to analyse the WQI of the Rourkela city in the dry seasons. The calculated score of BCWQI records a value between 2 and 95, indicating water quality as good – poor category for human consumption. All other parameters have surpassed the standard permitted value, except for the PO_4^{3-}, Fe^{2+}, K^+ and pH parameters. Location V – (5), and (8 - 10) had the highest pollution levels, indicating regional pollution hotspots. The EC, TDS, alkalinity, and hardness measurements of maximum sampling sites, show the largest exceedance and deviation, with a value of > 95% in the dry season. The results show considerable location – dependent as well as seasonal changes, which are influenced by natural and anthropogenic factors. Water quality classification reveals 40% of the water corresponds towards excellent – fair drinking quality. Remaining 60% (Figure 4a) conferred as borderline to Poor class, that correspond to higher pollution levels, which may be

BCWQI			
WQI Classification	**Quality of water**	**Number of samples**	**% of total samples**
0 - 3	Excellent	1	10
4 to 17	Good	1	10
18 - 43	Fair	2	20
44 - 59	Border line	2	20
60 -100	Poor	4	40
CCME-WQI/CWQI			
95 - 100	Excellent	1	10
80 - 95	Good	3	30
65 - 79	Fair	2	20
45 - 64	Marginal	3	30
0 - 44	Poor	1	10
AWQI			
< 50	Excellent	1	10
50 - 100	Good	1	10
100 - 200	Poor	3	30
200 - 300	Very Poor	1	10
> 300	Unsuitable	4	40
MWQI			
0 - 25	Very Poor	1	10
26 - 50	Poor	2	20
51 - 70	Fair	4	40
71 - 80	Good	2	20
81 - 100	Excellent	1	10
OWQI			
0 - 59	Very Poor	1	10
60 - 79	Poor	3	30
80 - 84	Fair	2	20
85 - 89	Good	2	20
90 - 100	Exceptional	2	20

Table 1. Classification and Suitability of the surface water samples for drinking purposes in terms of different water quality methods.

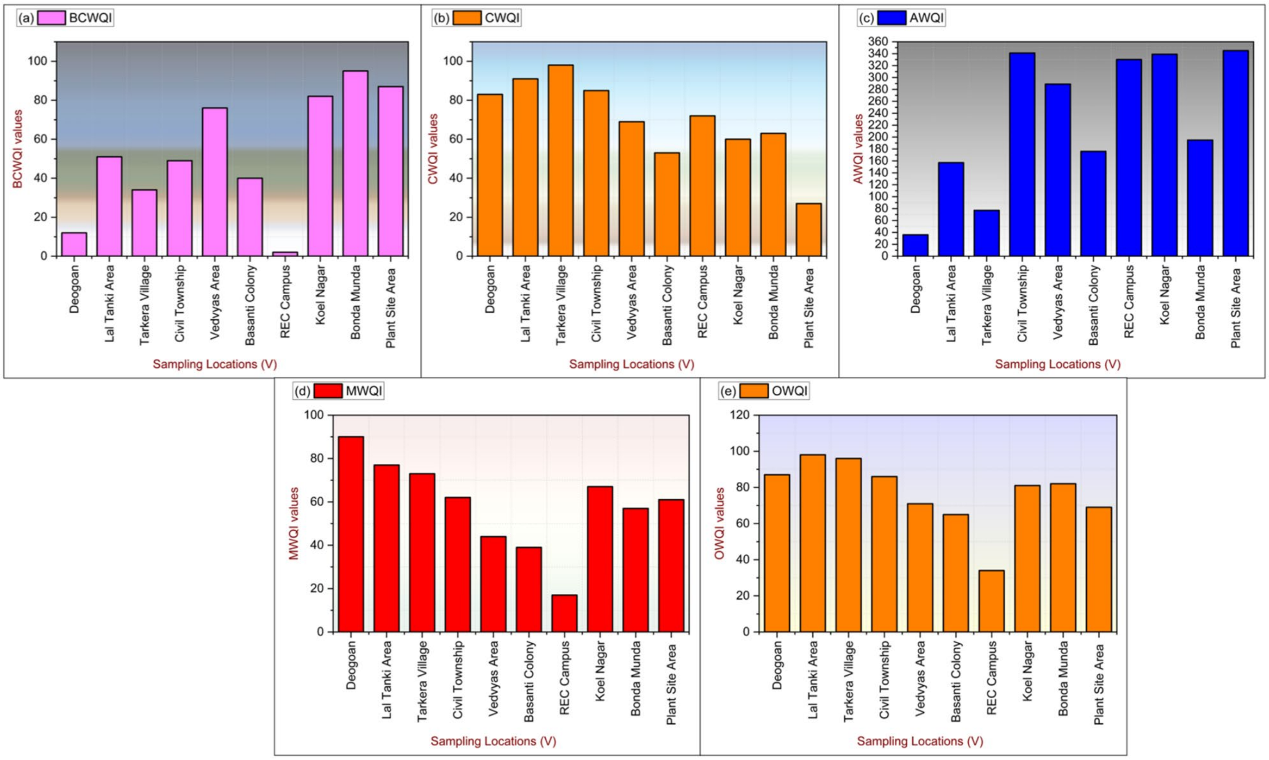

Fig. 3. Bar diagrams showing the calculated scores of various water quality indices (**a**) BCWQI, (**b**) CWQI, (**c**) AWQI, (**d**) MWQI, and (**e**) OWQI.

caused by monsoon runoff and other influxes of pollutants. As a result, the river's BCWQI, with an average index value of 52.80, is in the "Borderline" water quality category. However as pointed out by[19], there are restrictions on how the BCWQI can be applied to evaluate a river's or watershed's water quality. Therefore, when assessing the outcomes, it is important to keep in mind the limits of the index to safeguard the aquatic resources[31].

Quality assessment utilizing CCME-WQI

The CCME/C WQI is a very useful instrument for keeping an eye on environmental trends and preserving species that are at risk. The public, stakeholders, and policymakers can all benefit from this segment-specific WQI, which offers insightful data on the quality of the water in particular areas. The following five categories such as: Excellent: 95–100; Good: 80–95; Fair: 65–79; Marginal: 45–64; and Poor: 0–44, apply to the assessment results (Table 1). This classification shows that the water quality is continuously below ideal or natural standards, putting it at risk. The current investigation reveals an expanded range of 27 to 98 (Figure 3b). The water quality classification indicate excellent to poor class. During the pre-monsoon season, the greatest value recorded at the site V – (3). The Rourkela City river's CWQI computation values are shown in Figure, which compares 12 water quality metrics to standard objective values. The analysis of percentage (Figure 4b) of city's CWQI values are defined as: 10% (excellent), 30% (good), 20% (fair), 30% (marginal), and 10% signify poor drinking water quality. Location-specific study reveals several important trends. The value ranging from 53 at location (6) to a peak of 72 at location (7), demonstrating significant seasonal variability. According to the assessment, V – (10) is severely contaminated throughout the dry season by EC, hardness, TDS, and alkalinity. New hotspots formed during the season, particularly at sites V – (6), (8), and (9), indicating pollutant influx. It highlights a combination of geogenic mobilization and anthropogenic intensification in the surface water system[94]. The CWQI variations validate these results, bolstering the proof of rising pollution levels during the test period.

Quality assessment utilizing AWQI

The AWQI values for 10 segments along the city are displayed in Figure 3c and (Table 1). The data indicates that the water quality at all sites is categorized as "Excellent to Unsuitable" water quality. This classification is consistent with the research conducted by[69] and[67]. The calculated AWQI score for the current research varied as 36 -345, depicting excellent to unsuitable water quality classification (Figure 3c). Site V – (10) has the highest AWQI value (345) during the examined time period, while V – (1) has the lowest (36) value. This implies that the water in location 10 is unsuitable for domestic use or drinking. A common geogenic source, maybe bolstered by seasonal redox reactions, is confirmed by the strong EC-alkalinity association. According to the percentage of distribution of water categorization (Figure 4c), the AWQI is distinguished into following types: excellent (10%), good (10%), poor (30%), very poor (10%), and unsuitable (40%). On the other hand, sites V –(7), (8), and (4) has the elevated AWQI value. The weathering of lateritic and gneissic rocks is responsible for the continuously high

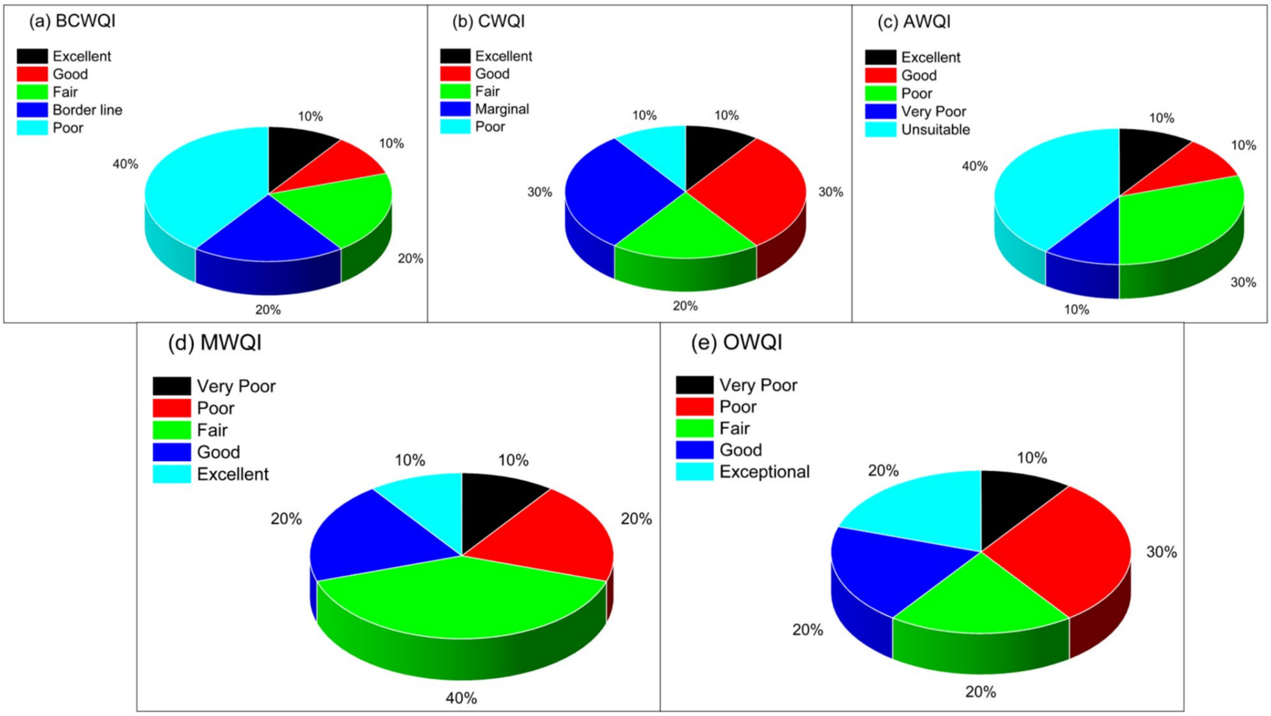

Fig. 4. Percentage of water quality classification representing rating of water quality: (**a**) BCWQI, (**b**) CWQI, (**c**) AWQI, (**d**) MWQI, and (**e**) OWQI.

amounts of dissolved solids and conductivity. These characteristics are released into the surface water by these rocks under lowering aquifer conditions. At the same time, at places V – (2) and (6), alkalinity and TH shows a significant rise, indicating surface inputs from pesticides, fertilizers, or runoff from adjacent saltpan operations. This suggests that there are greater restrictions on the usage of water for residential use during the rainy season. An anthropogenic origin is supported by the spatial overlap between these locations and areas that produce salt or agriculture[95]. Recent data show that rising development and climate change are posing serious pollution concerns for the Brahmani River at 8 sample water locations. Its water quality is therefore rated as "Poor – Very Poor - Unsuitable" in the AWQI ratings.

Quality assessment utilizing MWQI

The MWQI was created by the Malaysian Department of Environment to quantify river water quality and to put safeguards in place for aquatic ecosystems[27]. Among the five categories represented in (Table 1), were used to classify water quality and indicated as: very poor (0-25), poor (26-50), fair (51-70), good (71-80), and excellent (81-100). A higher MWQI number implies better water quality, whereas a lower value indicates poorer water quality,the MWQI is a numerical indicator. Throughout the research, the obtained value ranged between 17 and 90, demonstrating a notable decline in surface water quality as a result of seasonal hydrological fluctuations. Figure 3d displays the MWQI values in this investigation. The water quality is rated as “Excellent” at V – (1), which also has the highest MWQI value at 90. While sites (4), (8), (9), and (10) have “fair” water quality, suggesting a sudden influx of pollutants. However, V - (7)'s MWQI value of 17 during the dry season places it in the “Very Poor” category, suggesting a combination of inputs from the use of agrochemicals and leaching. Relying on the classification of drinking water quality, 30% of water samples corresponds towards poor – very poor; 40% as fair; and 30% indicated as excellent to good water quality (Figure 4d). According to the MWQI during the testing period, locations (2) and (3) once again have the elevated MWQI values at 77 and 23, respectively, illustrating good water. The influence of monsoonal runoff in mobilizing surface and subsurface contaminants is highlighted by the temporal increase in AWQI values across multiple locales[13]. Results from the Malaysia Water Quality Index show that the city’s water is categorized as "Excellent – Very Poor" by Malaysian standards. Based on this categorization, it seems like the water is used for drinking and irrigation, with prior treatment.

Quality assessment utilizing OWQI

Remarkably, the Gelsey et al.[70], observes that the OWQI is still being used by Oregon State in the US to evaluate surface water quality and prevent environmental damage. The ten water specimens along the Rourkela City are designated as having "Exceptional – Very Poor" water quality according to the analytical results of the OWQI (34 – 98), given in Figure 3e and Table 1. The OWQI results show that during the dry season, V –(7) has the lowest value (34), while V –(2) has the highest value (98). Elevated scores at V –(7) can be attributed to hydrogeochemical processes that enhance heavy metal mobilization. Heavy rainfall accelerates the leaching of Cu^{2+} and Zn^{2+} from lateritic and gneissic formations, while clay-rich layers, which temporarily trap metals, release them during intense recharge events[96]. Additionally, at V – (10), rapid monsoon infiltration increases metal dispersion while decreasing residence time and permitting pollutants to survive by encouraging surface water mixing between shallow and deep aquifers. Both segments fall under the category of "Exceptional - Very Poor" quality, as indicated in five categories: very poor (0–59), poor (60–79), fair (80–84), good (85-89), and exceptional (90–100)[55]. Particularly, based on percentage of classification of water, around 40% indicate poor water,20% as fair and remaining 40% points towards exceptional – good water quality (Figure 4e). The results draw attention to the significant effects of seasonal variations, particularly pre-monsoons, on elevated EC, TH, and TDS and heavy metal contamination. Seasonal variability rises at key points emphasize the significance of focused monitoring and mitigation measures to deal with the causes of pollution[97]. To maintain water quality and reduce the health risks related to heavy metal exposure in the affected areas, thorough and ongoing monitoring is necessary. In order to lessen seasonal contamination surges, this analysis highlights the importance of putting in place appropriate pollution management techniques[98],[99].

Comparison of different water quality indices (WQIs)

Water Quality Indices (WQIs) are essential tools that simplify the interpretation of complex environmental data by providing a single, quantifiable measure of water quality. A variety of WQIs, including the BCWQI, CWQI, AWQI, MWQI, and OWQI, have been created to meet different evaluation requirements and geographic situations. Each uses a unique methodology, scale, and classification system to evaluate surface water quality, making them suitable for distinct applications ranging from human consumption to agricultural use and ecosystem protection[100]. BCWQI (Brahmani Comprehensive Water Quality Index) is a region-specific index designed for assessing the Brahmani River system. It scores water quality from 0 (excellent) to 100 (poor), with categories: Excellent (0–3), Good (4–17), Fair (18–43), Borderline (44–59), and Poor (60–100). In the Rourkela city, BCWQI values ranged between 2 and 95 during the dry season, averaging 52.80, placing it in the Borderline category. High exceedances of EC, TDS, alkalinity, and hardness were recorded at multiple sites, indicating both seasonal and location-specific pollution driven by human and natural factors[101]. Although useful for rapid assessments, BCWQI's limitations—highlighted by Zandbergen and Hall[19], suggesting cautious interpretation when applied beyond its original design context.

Meanwhile, CWQI (Canadian Water Quality Index), developed by the CCME, assesses water quality using a reverse scoring system where higher values indicate better quality. Categories include: Excellent (95–100), Good (80–94), Fair (65–79), Marginal (45–64), and Poor (0–44). In Rourkela, CWQI ranged from 27 to 98, with 60% of samples rated Marginal to Poor. CWQI is particularly effective in environmental monitoring and policy-making, offering valuable insights into water quality trends and pollutant influxes during monsoon periods. AWQI (Agricultural Water Quality Index) is tailored to assess water usability for agriculture and domestic consumption. Scores ranged from 36 to 345 in Rourkela, falling into categories from Excellent to Unsuitable. Around 40% of the sites were classified as Unsuitable, with site V–(10) showing the highest level of contamination due to elevated EC and TDS. AWQI helps identify geogenic and anthropogenic contributions, such as rock weathering and agrochemical runoff, making it highly effective in agricultural zones and areas affected by industrial effluents.

Moving forward, the Malaysian DOE (Department of Environment) created the MWQI (Malaysian Water Quality Index), which classifies water quality as Very Poor (0–25), Poor (26–50), Fair (51–70), Good (71–80), and Excellent (81–100). The MWQI range in Rourkela was between 17 and 90, highlighting severe degradation at some sites (e.g., V–(7)) and good quality at others (e.g., V–(1)). This index is ecosystem-focused and integrates various pollution parameters, making it suitable for ecological conservation efforts and policy regulation[102]. OWQI (Oregon Water Quality Index), still in use in the U.S., also ranges from 0 to 100, with categories: Very Poor (0–59), Poor (60–79), Fair (80–84), Good (85–89), and Exceptional (90–100). In the Rourkela study, OWQI values ranged from 34 to 98. Around 40% of samples were rated as Exceptional–Good, 20% as Fair, and 40% as Poor–Very Poor. OWQI effectively captured heavy metal mobilization and the impact of monsoonal infiltration on surface–subsurface interactions, providing strong evidence of pollution dynamics driven by hydrogeochemical processes[103].

As a result, Each WQI serves different analytical purposes. BCWQI and CWQI are ideal for broad environmental assessments. AWQI emphasizes agricultural and domestic utility, while MWQI focuses on ecological health. OWQI excels in tracking pollution from geogenic and hydrological processes. Together, they offer a holistic view of water quality across spatial and seasonal gradients, underscoring the need for integrated water resource management and targeted pollution control measures.

Comparison with future studies

A summary of earlier research on the use of WQI in different rivers may be found in Table 2. Different WQI assessments have been conducted on various rivers; the most widely used indices are described below.

Being a riverine nation, India is highly dependent on its vast river system for daily water use, transportation, agriculture, and fishing. However, rapid industrialization, urban expansion, and unregulated waste disposal have led to a significant deterioration of river water quality. This study provides a comparative assessment of water quality across several key rivers, utilizing various water quality indices (WQIs) such as the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI), Assigned Water Quality Index (AWQI), Malaysian Water Quality Index (MWQI), Oregon Water Quality Index (OWQI), and others. The findings reveal a concerning pattern of water degradation across all sampled rivers, with most being classified under poor or unsuitable quality categories.

The Karnaphuli River in Chittagong, a major waterway in southeastern Bangladesh, was assessed using the CCME WQI and classified as "Poor." According to Mukut et al.[104], the degradation in water quality is primarily

SN	River Name	State	WQI	Rank	Results	References
1	Damodar River	West Bengal	CCME WQI	Poor	Runoff, industrial waste, and municipal trash were all factors in the contamination. You cannot put water for any purpose	[104]
2	Shitalakshya River	Narayanganj	CCME WQI	Poor	Human activity and industrial waste are the primary causes of pollution. No good for farming, drinking, or fishing. When compared to the monsoon season, the water quality in the winter is extremely poor	[105]
			AWQI	PTBU		
3	Jamuna River	Tangail	AWQI	Unsuitable	Possible sources of contamination include industrial effluents, runoff, anthropogenic activities, and the discharge of municipal wastewater. It is necessary to treat the water properly before using it	[106]
			MWQI	PTBU		
			OWQI	Very poor		
4	Dhaleshwari River	Tangail	CCME WQI	Poor	Industrial and municipal wastewater, including tannery effluent, sewage, runoff, and others, are the primary sources of pollution. In comparison to the monsoon season, the water quality is significantly lower all winter long	[107]
			OWQI	PTBU		
5	Turag River	Gazipur	WQI	PTBU	Pollutants primarily originate from human activities, sewage overflow, industrial effluent, and runoff	[108]
6	Old Brahmaputra River	Mymensingh	MWQI	Very Polluted	Wastewater treatment plants, industrial waste, industrial runoff, and other related sources account for the vast bulk of pollution. Only irrigation should be done with this water	[109]
7	Halda River	Chittagong	BCWQI	Poor	The origins of the river's contamination were identified through the use of a structured questionnaire survey in conjunction with direct observation. The interviewees found industrial waste (53%), sewage contamination (20%), tobacco farming (13%), a rubber dam (8%), and sand extraction (6%). The Halda river is the biggest natural breeding site for carps in the country.	Nath et al.[110]
			CCME	Poor		
			AWQI	Unsuitable		
			MWQI	Bad		
			OWQI	Very poor		

Table 2. A list of the WQI comparisons of various rivers.

attributed to industrial discharges, municipal solid waste, and surface runoff. The water is deemed unsuitable for any intended use, highlighting the severity of contamination in this region.

Similarly, the Shitalakshya River in Narayanganj also received a "Poor" rating under the CCME WQI. Chowdhury et al.[105] report that anthropogenic activities, especially from industrial sources, are the predominant contributors to pollution. Seasonal variation is evident, with water quality deteriorating substantially during the winter season when river flow is minimal. This seasonal influence underscores the need for continuous monitoring and adaptive management strategies.

The Jamuna River in Tangail was evaluated using multiple indices, including AWQI, MWQI, and OWQI. It was rated as "Unsuitable" under AWQI and "Very Poor" under OWQI, with MWQI classified as "Poor to Be Used (PTBU)." The primary sources of contamination include effluents from nearby industries, agricultural runoff, and municipal wastewater[106]. Despite being one of the major transboundary rivers in the region, the Jamuna's deteriorating water quality necessitates urgent intervention to safeguard ecological and human health.

The Dhaleshwari River, another critical river in the Tangail district, similarly shows poor water quality, especially during winter. Using the CCME WQI, it was categorized as "Poor," while the OWQI indicated "Poor to Be Used." Hasan et al.[107] identify industrial discharges, particularly from the tannery sector, as a major contributor to pollution. Municipal sewage and surface runoff further exacerbate the water quality, particularly during the dry season when dilution capacity is low.

In Gazipur, the Turag River was assessed using general WQI metrics and found to be in the "Poor to Be Used" category. Pollution sources include a combination of industrial effluent, sewage overflows, and urban runoff[108]. The river, which once supported aquatic biodiversity and community livelihoods, is now heavily impacted by anthropogenic pressures.

The Old Brahmaputra River in Mymensingh was evaluated using the MWQI, receiving a classification of "Very Polluted." Muyen et al.[109] attribute the high pollution load to untreated wastewater discharges, industrial waste, and runoff from adjacent urban areas. The water is now only deemed suitable for irrigation, indicating its limited usability due to high contamination levels.

The Halda River, also located in Chittagong, presents a unique case. Despite being the country's most significant natural breeding ground for carps, its water quality is under severe stress[110]. Multiple indices—including WAWQI, BCWQI, CCME WQI, AWQI, MWQI, and OWQI—uniformly classify it under "Unsuitable," "Poor," or "Very Poor" categories. Based on data from a recent structured questionnaire and field observations, industrial waste accounts for 53% of the pollution sources, followed by sewage (20%), tobacco farming (13%), rubber dam construction (8%), and sand extraction (6%). These activities pose a serious threat to the ecological integrity of the river, especially its critical function as a breeding ground for native fish species.

Overall, the assessment of these seven rivers demonstrates a consistent trend of water quality degradation across different regions and seasons. According to the findings of the WQI assessments, the majority of these rivers are contaminated and fall into the lowest water quality category[95]. The authors of this study claim that runoff, human activity, municipal wastewater, and industrial effluent are the primary sources of contamination[48]. Seasonal fluctuations further influence water quality, with winter months showing particularly poor readings due to reduced flow and dilution capacity[98]. The widespread classification of these rivers as "Poor," "Unsuitable," or "Very Polluted" by various WQI methodologies demonstrates the pressing need for measures and protections to improve these rivers' poor water quality, as they are vital community water sources[73]. Without immediate action, the continued degradation of these critical water bodies will pose escalating risks to human health, biodiversity, and sustainable development. Establishing the required standards and guidelines is essential given the importance of surface water as a local source of water for the measurement of WQI of surface water quality. Consequently, it is essential to thoroughly assess the current state of water quality, identify the causes of contamination, and implement the required regulations in order to ensure the improvement and preservation of water resources.

Implications of the study

This study presents critical insights into the current status and long-term challenges facing the Brahmani River in Odisha, offering significant implications for water resource management, ecological sustainability, and regional development planning[68]. By examining hydro-chemical parameters over a three-year period (2022–2025) and applying multiple Water Quality Index (WQI) models namely, BCWQI, AWQI, CWQI, MWQI, and OWQI, the innovative assessment provides a comprehensive, multi-dimensional assessment of surface water quality that goes beyond conventional evaluation methods. One of the most pressing implications is the confirmation that the Brahmani River is undergoing seasonal and spatial degradation, mostly caused by poor waste management techniques, urbanization, agricultural runoff, and industrial effluents[111]. The deterioration in parameters such as pH, TDS, EC, heavy metals (Cu^{2+}, Zn^{2+}, Pb^{2+}), and nutrient levels highlights the cumulative impact of anthropogenic activities on surface water systems[95]. The classification of approximately 40% of river water as "inadequate" for use (based on Canadian WQI values ranging between 27 and 98) is a clear signal that current pollution control measures are insufficient.

Ecologically, the degradation has direct consequences on the river's biodiversity—particularly its function as a spawning ground for carp and other aquatic organisms[21]. The observed decline in oxygen levels, combined with increased concentrations of toxic substances and a significant reduction in plankton populations, points to a disrupted aquatic food chain. This poses a serious threat to fisheries, which are vital for the food security and livelihoods of local communities. The 20% decadal population growth in Rourkela further amplifies the urgency, as increasing water demand and waste generation compound the stress on the river ecosystem[63]. From a governance perspective, the study underscores the need for robust, science-based interventions. Immediate steps are required to implement sustainable water treatment infrastructure, enforce pollution control regulations, and promote eco-friendly agricultural and industrial practices[112]. The recommendation to adopt advanced technologies—such as machine learning, hydro-chemical mapping, and land-use analysis—offers a practical path forward to enable predictive modelling and targeted remediation efforts[60]. These technologies will be instrumental in identifying pollution hotspots and prioritizing interventions.

According to the study, local water governance should be in line with the United Nations Sustainable Development Goals (SDGs), particularly SDG 6 (Clean Water and Sanitation), SDG 14 (Life Below Water), and SDG 11 (Sustainable Cities and Communities). Ensuring safe water access and ecosystem resilience will contribute not only to environmental health but also to public well-being and economic stability[18]. Another important implication is the call for multi-stakeholder engagement. Long-term river management success hinges on coordinated actions involving governmental agencies, local authorities, industries, civil society, and scientific institutions. Policymakers are encouraged to utilize this study's findings to develop locally adapted strategies that bridge science and policy and promote inclusive, evidence-based decision-making[56]. In this perspective, this work serves as a crucial foundation for transformative water governance in Odisha. It advocates for a holistic, data-driven, and participatory approach to restoring the Brahmani River, safeguarding its ecological integrity, and securing water resources for future generations.

Limitations

While the study offers valuable insights into surface water quality dynamics in Rourkela City and proposes a range of brownie points, several limitations should be acknowledged.

(a) The analysis primarily focuses on surface water parameters and does not comprehensively integrate groundwater quality data, which limits the understanding of the complete hydrological system. Additionally, although spatiotemporal trends were assessed, the monitoring network was limited in terms of both geographic coverage and sampling frequency, potentially restricting the resolution and accuracy of temporal variation analysis.

(b). This study is limited to pre-monsoon season data, and the lack of multi-seasonal monitoring restricts the ability to capture seasonal variations in pollution levels.

(c) The study also relied heavily on secondary data and standard water quality indices (WQIs), which may not fully capture localized pollution events or emerging contaminants such as microplastics or pharmaceutical residues. Furthermore, while water quality techniques were utilized, these approaches depend on data quality and may not perform optimally in data-scarce environments.

(d) This study did not highlight the longitudinal assessments covering pre-monsoon, monsoon, and post-monsoon periods to better understand temporal shifts in water quality.

(e) Another limitation lies in the absence of socioeconomic data integration. Factors such as population growth, land-use change, and industrial expansion, which significantly influence water quality, were not explicitly modelled.

(f) Integrating real-time water quality monitoring systems, hydrological modelling, and AI-driven predictive analysis would enhance water resource management strategies.

(g) Similarly, while the recommendations highlight international collaboration and policy development, the feasibility of implementing these measures in a local context—given administrative, financial, and technological constraints—was not assessed.

(h) Lastly, climate change impacts were acknowledged but not quantitatively examined. Longitudinal studies are needed to better understand the long-term implications of these recommendations under varying climate scenarios.

By addressing these challenges in future research, the sustainability of the Brahmani River can be safeguard for future generations, and would help in strengthening the scientific basis for sustainable water resource management in the Rourkela City and similar semi-urban regions; ensuring it continues to serve as a vital water resource for drinking, agriculture, industry, and biodiversity in the region.

Conclusion

The water quality of the Brahmani River, Odisha, varies seasonally, heavily influenced by industrial operations and urban development. The study investigates the hydro-chemical characteristics and predictive water quality modelling of surface water quality for a detection period of 3 years (2022 – 2025), through the application of BCWQI, AWQI, CWQI, MWQI, and OWQI models. The pH levels varied from 5.33 – 7.06, falling within the permitted range of 6.5 to 8.5. It indicates water samples is acidic to slightly alkaline. Higher TDS values indicate an increase in dissolved chemicals, which could negatively impact water quality. EC pollution typically stems from industrial discharge and agricultural runoff. Elevated heavy metals concentration suggesting insufficient oxygen for a healthy aquatic ecosystem. Observations from ten monitoring segments reveal that, during pre-monsoon season, critical parameters including conductivity, total dissolved solids, hardness, alkalinity, Cu^{2+}, Zn^{2+}, and Pb^{2+}, frequently surpass the standard limits established by WHO (2017). It showed signs of anthropogenic influence, notably from agricultural activities. The results underscore both the natural mineralization process and emerging pollution risks in the aquifer.

Through the application of BCWQI (2 – 95), the main hydro-chemical processes were identified in six locations, distinguishing between carbonate dissolution and anthropogenic contributions such as nutrient leaching. Conducting assessments of the Water Quality Index (27 – 98) based on Canadian approach, classifies the river's water quality as inadequate, accounting around 40%, underscoring the significant relationship between these parameters and the deteriorating state of surface water. According to the AWQI categorization, the declining quality of the Rourkela city's water renders it unfit for human consumption and household purposes in 8 monitoring locations such as V – (2), and (4 – 10). On the basis of Malaysian (value obtained = 17 – 90) and Oregon (value obtained = 34 – 98) methods, key contributors to pollution encompass industrial waste, open defecation, and runoff from urban and agricultural regions, resulting in an ongoing deterioration of water quality. The presence of heavy metals, toxic chemicals, and organic pollutants has significantly disturbed the ecological balance of the river, which is essential for carp spawning. With a decadal population growth rate of roughly 20%, the city is growing in several directions. This is mostly dependent on specific environmental factors, such as temperature, pH, alkalinity, EC, TH, TDS, water cleanliness, and adequate river flow caused by the monsoon. The impact of pollution has profoundly transformed these conditions, leading to habitat destruction, diminished oxygen levels, and heightened mortality rates among fish eggs and larvae. Moreover, the reduction in plankton populations, which serve as a crucial food source for juvenile carp, has increasingly threatened the productivity of the river's fishery. As a result, quick and persistent work is required to restore the water quality of the Brahmani River and ensure its safety for domestic, agricultural, and ecological purposes. Restoring the river's ecological integrity requires the implementation of comprehensive water treatment strategies, including regular filtration and continuous monitoring to assess and maintain water quality standards suitable for human consumption. In addition, the government must adopt proactive and science-based rehabilitation measures to address pollution sources and mitigate further degradation.

From a broader perspective, the results have significant implications for achieving SDGs. Special attention should be given to preserving the river's role as a critical breeding ground for carp and other aquatic species, which are vital to the region's biodiversity and local livelihoods. Ensuring the sustainable management of the Brahmani River is not only essential for environmental health but also for supporting the socio-economic well-being of communities that depend on it. The incorporation of advanced tools such as machine learning algorithms, hydro-chemical mapping, and land use data will further strengthen the decision – making foundation for surface water protection. A coordinated effort among governmental bodies, local stakeholders, and environmental agencies is crucial for long-term success. By linking science to policy, this study contributes to the development of locally adopted strategies for the protection and resilience of surface water resources in Odisha.

Recommendations

Based on the comprehensive analysis of surface water quality parameters and the spatiotemporal trends observed in the Rourkela City, the following recommendations are proposed to address the identified issues and enhance the management of surface water resources:

(a) Sustainable Extraction: Implement controlled extraction policies to prevent over- exploitation of groundwater resources, ensuring that withdrawal does not exceed the recharge rate.
(b) Industrial Regulation: Enforce stricter regulations on industrial discharges, particularly from steel industries, to prevent the contamination of surface water with harmful substances like EC, TDS, TH, and heavy metals.
(c) Agricultural Practices: Promote the use of environmentally friendly agricultural practices, including the judicious use of nitrogen fertilizers, to reduce the leaching and other contaminants into the surface water.
(d) Water Treatment: Establish water treatment facilities that can address the specific contaminants identified in the study, ensuring that water meets WHO guidelines for both drinking and irrigation purposes.

(e) Monitoring and Data Analysis: Continue the use of different models and other data mining methods to monitor surface water quality. Expand the monitoring network to include more sites and increase the frequency of sampling to capture temporal variations more accurately.
(f) Public Awareness and Education: Increase awareness among local communities and stakeholders about the importance of groundwater conservation and the impact of their activities on water quality.
(g) Policy Development: Develop comprehensive water management policies that integrate findings from WQIs and other scientific studies, focusing on long-term sustainability. In addition to the overall policy framework, it is essential to incorporate actionable, region-specific measures that directly address local environmental pressures. Such measures may include implementing effluent-reuse policies tailored to industrial and agricultural sectors, establishing green-buffer zoning along riverbanks to reduce pollutant runoff, strengthening watershed-level conservation programs, and adopting region-appropriate groundwater recharge practices.
(h) International Collaboration: Seek international expertise and collaboration for technology transfer and capacity building in surface water management, especially in developing countries like China and Iran.
(i) Groundwater Recharge: Invest in artificial recharge projects to enhance the natural replenishment of aquifers, especially in areas where the water table is declining.

Future research should conduct longitudinal studies to assess the efficacy of these treatments, investigate alternative water purification technologies, and evaluate the influence of climate change on surface water quality. Additionally, policymakers must consider revising agricultural practices and implementing stricter regulations on industrial discharges to preserve the integrity of surface water resources. Collaborative efforts between researchers, local authorities, and communities are essential to develop adaptive strategies that ensure the long-term sustainability of water resources in arid regions.

Data availability
The analyzed data supporting the findings of this study are provided in the manuscript and can also be obtained from the corresponding author upon request.

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References
1. Egbueri, J. C., Agbasi, J. C., Khan, M. Y. A., Abba, S. I., Turki, A. F., & ElKashouty, M. Assessing the environmental, health, and food security Implications of heavy metals in irrigation water: a multi-index analytical framework. Analytical Letters 1-36. (2025)
2. Ghimire, M. et al. Hydrogeochemical characterization of shallow and deep groundwater for drinking and irrigation water quality index of Kathmandu Valley Nepal. *Environ. Geochem. Health* **47**(3), 61 (2025).
3. Jat Baloch, M. Y. et al. Evolution mechanism of arsenic enrichment in groundwater and associated health risks in southern Punjab Pakistan. *Int. J. Environ. Res. Public Health* **19**(20), 13325 (2022).
4. Mohammed, M. A., Szabó, N. P., Mikita, V. & Szűcs, P. Spatiotemporal evaluation of irrigation groundwater quality in Hungarian agricultural sites using hydrochemical and machine learning approaches. *Discov. Appl. Sci.* **7**(8), 1–23 (2025).
5. Ali, A. et al. Advanced satellite-based remote sensing and data analytics for precision water resource management and agricultural optimization. *Sci. Rep.* **15**(1), 27527 (2025).
6. Aluma, V. C., Igwe, O., Omeka, M. E., & Anyanwu, I. E. Combining multiple numerical and chemometric models for assessing the microbial and pollution level of groundwater resources in a shallow alluvial aquifer, Southeastern Nigeria. Arabian Journal of Geosciences, **17**(7), 206 (2024).
7. Chidiac, S., El Najjar, P., Ouaini, N., El Rayess, Y. & El Azzi, D. A comprehensive review of water quality indices (WQIs): history, models, attempts and perspectives. *Rev. Environ. Sci. Bio/Technol.* **22**(2), 349–395 (2023).
8. Nikoo, M. R. et al. Mapping reservoir water quality from Sentinel-2 satellite data based on a new approach of weighted averaging: Application of Bayesian maximum entropy. *Sci. Rep.* **14**(1), 16438 (2024).
9. Pandey, J. G., Gaurav, K., Singh, A. K. & Kumar, A. Just transition beyond extraction: a spatial and comparative case study of two coal mining areas in India. *Energy Res. Soc. Sci.* **126**, 104136 (2025).
10. Johnston, N. Developing indices for agricultural water quality (Doctoral dissertation, CQUniversity). (2025)
11. Muniz, D. H. & Oliveira-Filho, E. C. Multivariate statistical analysis for water quality assessment: a review of research published between 2001 and 2020. *Hydrology* **10**(10), 196 (2023).
12. Islam, R. et al. Integrated evaluation of groundwater hydrochemistry using multivariate statistics and irrigation-based water quality indices. *Sci. Rep.* **15**(1), 24923 (2025).
13. Camara, M., Jamil, N. R., Abdullah, A. F. B., Binti Hashim, R. & Aliyu, A. G. Economic and efficiency-based optimisation of water quality monitoring network for land use impact assessment. *Sci. Total Environ.* **737**, 139800 (2020).
14. Jat Baloch, M. Y. et al. Groundwater contamination, fate, and transport of fluoride and nitrate in Western Jilin, China: Implications for water quality and health risks. *Environ. Chem. Ecotoxicol.* **7**, 1189–1202 (2025).
15. Das, A. Monsoonal impacts on water quality in the Baitarani River, Odisha: a comprehensive evaluation using water quality indices, multivariate statistics, and machine learning models for sustainable pollution control. Green Technology, Resilience, and Sustainability. (2025a)
16. Sajib, A. M. et al. Developing a novel tool for assessing the groundwater incorporating water quality index and machine learning approach. *Groundwater Sustai. Dev.* **23**, 101049 (2023).
17. Swain, L. G. The evolution of the Canadian (CCME) water quality index. *Water Qual. Res. J.* **59**(4), 342–346 (2024).
18. Talukdar, S. et al. Optimisation and interpretation of machine and deep learning models for improved water quality management in Lake Loktak. *J. Environ. Manage.* **351**, 119866 (2024).
19. Zandbergen, P. A. & Hall, K. J. Analysis of the British Columbia water quality index for watershed managers: a case study of two small watersheds. *Water Qual. Res. J.* **33**(4), 519–550 (1998).
20. Ansari, Z. Z., Vorina, A., Kojić, D., Dupláková, D. & Duplák, J. Assessing the suitability of CCME WQI as a groundwater quality monitoring tool: an environmental ergonomics case analysis. *Appl. Sci.* **14**(16), 7325 (2024).
21. Carvalho, W. D. S., Filho, F. J. C. M., Rodrigues, L. R. & Calheiros, C. S. C. Influence of land use and land cover on the quality of surface waters and natural wetlands in the Miranda River Watershed Brazilian Pantanal. *Appl. Sci.* **14**(13), 5666 (2024).

22. Jat Baloch, M. Y., Su, C., Talpur, S. A., Iqbal, J. & Bajwa, K. Arsenic removal from groundwater using iron pyrite: influence factors and removal mechanism. *J. Earth Sci.* **34**(3), 857–867 (2023).
23. Kükrer, S. & Mutlu, E. Assessment of surface water quality using water quality index and multivariate statistical analyses in Saraydüzü Dam Lake Turkey. *Environ. Monit. Assess.* **191**(2), 71 (2019).
24. Haidery, A., Umar, R. & Khan, I. Seasonal variation and spatial distribution of heavy metal (loid) s concentration in groundwater and surface water from hard-rock terrain, Ranchi, India. *Environ. Dev. Sustain.* **27**(8), 18591–18625 (2025).
25. Das, A. Drinking water resources suitability assessment in Brahmani River Odisha based on pollution index of surface water utilizing advanced water quality methods. *Sci. Rep.* **15**(1), 34101 (2025).
26. Iqbal, J., Amin, G., Su, C., Haroon, E. & Baloch, M. Y. J. Assessment of landcover impacts on the groundwater quality using hydrogeochemical and geospatial techniques. *Environ. Sci. Pollut. Res.* **31**(28), 40303–40323 (2024).
27. Arman, N. Z. et al. Water quality assessment of Johor River Basin, Malaysia, using multivariate analysis and spatial interpolation method. *Environ. Sci. Pollut. Res.* **32**(4), 1766–1782 (2025).
28. Low, M. L. et al. Advancing sustainable water quality monitoring and remediation in malaysia: innovative analytical solutions for detecting and removing emerging contaminants. *ACS ES&T Water* **4**(11), 4758–4773 (2024).
29. Das, A. Geographical Information System–driven intelligent surface water quality assessment for enhanced drinking and irrigation purposes in Brahmani River, Odisha (India). *Environ. Monit. Assess.* **197**(6), 629 (2025).
30. Ranjan, A. K., Sahoo, K. K., Manasa, P., & Gorai, A. K. Assessing the role of urban expansion in an industrial city (Rourkela, India) on land use/land cover dynamics and its impacts on aerosols and land surface temperature. Journal of the Indian Society of Remote Sensing, 1-22. (2025)
31. Tiwari, A., Hsuan, E., & Goswami, S. Spatiotemporal water quality assessment in spatially heterogeneous horseshoe Lake, Madison County, Illinois Using Satellite Remote Sensing and Statistical Analysis (2020–2024). (2025)
32. Das, A. Harnessing hydro chemical characterization of surface water using water quality indices and machine learning–driven water quality modelling with special emphasis on side–stream pollution. Desalination and Water Treatment 101592. (2025i)
33. Nayak, A. & Kar, A. K. Mapping and monitoring of LULC change dynamics in industrial Cities in Odisha, India, Using Google Earth Engine. *J. Urban Planning Dev.* **151**(4), 05025034 (2025).
34. Murkute, Y., Hota, S. R., Hota, R. N., Goswami, S. & Das, R. Nitrate nightmares: nitrate contamination and health risks in a rapidly expanding City of Central India. *Water Air Soil Pollut.* **236**(1), 68 (2025).
35. Das, A. Evaluation of surface water quality in Brahmani River Basin, Odisha (India), for drinking purposes using GIS-based WQIs, multivariate statistical techniques and semi-variogram models. *Innov. Infrastruct. Solut.* **9**(12), 484 (2024).
36. Swain, R., Mishra, D., & Aditya, K. Unveiling Industrial Influence: Statistical Insights into Brahmani River Water Quality. In Mitigation and Adaptation Strategies Against Climate Change in Natural Systems (pp. 181-192). Cham: Springer Nature Switzerland. (2025)
37. Hussein, E. E. et al. Groundwater quality assessment and irrigation water quality index prediction using machine learning algorithms. *Water* **16**(2), 264 (2024).
38. Korrai, S., Reddy, N. S., Earle, M., Mediboyana, H., & Meruva, B. Community Perception on Groundwater Quality Versus Analytical Quality in the Coastal Areas of Visakhapatnam, India—Opinion Versus Actuality. In Conference of Innovative Product Design and Intelligent Manufacturing System pp. 165-174 Singapore: Springer Nature Singapore. (2023)
39. Palabıyık, S., & Akkan, T. Evaluation of water quality based on artificial intelligence: performance of multilayer perceptron neural networks and multiple linear regression versus water quality indexes. Environment, Development and Sustainability, 1-24 (2024).
40. Jafar, R. et al. Multiple linear regression and machine learning for predicting the drinking water quality index in Al-Seine Lake. *Smart Cities* **6**(5), 2807–2827 (2023).
41. APHA. *In: Standard methods for the examination of water and wastewater* 23rd edn. (American Public Health Association, 2017).
42. WHO, Guidelines for drinking-water quality. Fourth Edition Incorporating the Frst Addendum. World Health Organization, Geneva. (2017)
43. Karim, M. R. et al. A comprehensive dataset of surface water quality spanning 1940–2023 for empirical and ML adopted research. *Sci. Data* **12**(1), 391 (2025).
44. Gani, A. et al. Water quality index assessment of river Ganga at Haridwar stretch using multivariate statistical technique. *Mol. Biotechnol.* **67**(8), 3130–3153 (2025).
45. Ilić, P. et al. Exposure levels, health risks, spatially distribution, multivariate statistics and positive matrix factorization model of heavy metals from wild solid waste dumpsites. *Water Air Soil Pollut.* **235**(10), 648 (2024).
46. Suriadikusumah, A. et al. Analysis of the water quality at Cipeusing river, Indonesia using the pollution index method. *Acta Ecologica Sinica* **41**(3), 177–182 (2021).
47. Yeob, S. J. et al. Evaluation of long-term water quality trends and CCME-WQI applicability in agricultural watersheds of Korea. *Korean J. Soil Sci. Fertil.* **58**(2), 240–250 (2025).
48. Khan, M. H. R. B., Ahsan, A., Imteaz, M., Shafiquzzaman, M. & Al-Ansari, N. Evaluation of the surface water quality using global water quality index (WQI) models: perspective of river water pollution. *Sci. Rep.* **13**(1), 20454 (2023).
49. Shahrir, A. H., Salih, G. H. A., & Taha, A. T. B. Forecasting Future scenarios of water quality index in Selangor, Malaysia with United Nations sustainable development goals integration. In International Conference on Dam Safety Management and Engineering (pp. 305-316). Singapore: Springer Nature Singapore. (2023)
50. Lee, S., Jo, B. G., Lim, J., Lee, J. M. & Kim, Y. D. Assessment of climate change impacts on hydrology using an integrated water quality index. *Hydrology* **11**(11), 178 (2024).
51. Iqbal, J. et al. Prediction of nitrate concentration and the impact of land use types on groundwater in the Nansi Lake Basin. *J. Hazard. Mater.* **487**, 137185 (2025).
52. Shiretorova, V. G. et al. Current state of lake Kotokel (eastern Cisbaikalia, Russia): Hydrochemical characteristics, water quality, and trophic status. *Water* **17**(4), 545 (2025).
53. Nash, G. Evaluating water quality index models: advancing methods and applications for surface water quality assessment in a changing environment. SSRN 5141742. (2024)
54. Makumbura, R. K. et al. Advancing water quality assessment and prediction using machine learning models, coupled with explainable artificial intelligence (XAI) techniques like shapley additive explanations (SHAP) for interpreting the black-box nature. *Results Eng.* **23**, 102831 (2024).
55. Gupta, S. & Gupta, S. K. A critical review on water quality index tool: Genesis, evolution and future directions. *Ecol. Inform.* **63**, 101299 (2021).
56. Rajabova, N., Sherimbetov, V., Sadiq, R. & Farouk Aboukila, A. An assessment of collector-drainage water and groundwater—an application of CCME WQI model. *Water* **17**(15), 2191 (2025).
57. Iqbal, J. et al. Hydrogeochemical assessment of groundwater and suitability analysis for domestic and agricultural utility in Southern Punjab Pakistan. *Water* **13**(24), 3589 (2021).
58. Mahdi, I. Temporary assessment of the quality of tigris river water during the wet season in central iraq using the CCME WQI and irrigation indices Egyptian. *J. Aquat. Biol. Fish.* **29**(1), 1945–1963 (2025).
59. Das, C. R. & Das, S. Assessment of surface water quality for drinking by combining three water quality indices with their usefulness: case of Damodar River in India. *Water Air Soil Pollut.* **234**(5), 327 (2023).
60. Nerae, M. D., Zimale, F. A., Steenhuis, T. S. & Kebedew, M. G. Using two water quality indices for evaluating the health and management of a tropical lake. *Hydrology* **11**(12), 212 (2024).

61. Bilgin, A. (2024). Evaluation of water quality of coastal and groundwater of the Eastern Black Sea Basin, Turkey, using multivariate statistical analysis and water quality index. In World Environmental and Water Resources Congress 2024 (pp. 356-361).
62. Chai, J. et al. Multi-biological risk in groundwater-surface water system under landfill stress: Driven by bacterial size and biological toxicity. *J. Hydrol.* **636**, 131282 (2024).
63. Doychev, D., Gartsiyanova, K., Yordanova, G. & Taneva, L. Multiple factor analysis using water quality index scores and parameters as an approach for evaluating the environmental status of polluted lakes along the Black Sea coast of Bulgaria. *J. Bulgarian Geogr. Soc.* **52**, 37–57 (2025).
64. Sirunda, J., Oberholster, P. & Wolfaardt, G. Assessing the adverse effects of land use activities on the water quality of selected Sub-Saharan Africa Reservoirs using a combination of water quality indices. *Water Air Soil Pollut.* **233**(7), 267 (2022).
65. Baloch, M. Y. J., Baidya, P., Aryal, M., Yang, L., Iqbal, J., Ptak, M., & Liu, C. Fate and transport of viruses in the subsurface environment: a systematic review of pollution pathways in saturated and unsaturated porous media. Environmental Research 123163. (2025)
66. Agbasi, J. C. et al. Analytical examination of the nutritional status of drinking water resources: a first case application in Africa. *Anal. Lett.* **58**(15), 2609–2625 (2025).
67. Aydin, H., Ustaoğlu, F., Tepe, Y. & Soylu, E. N. Assessment of water quality of streams in northeast Turkey by water quality index and multiple statistical methods. *Environ. Forensics* **22**(1–2), 270–287 (2021).
68. Hashim, N. H. F. et al. Water Quality and prevalence of extended spectrum beta lactamase producing escherichia coli (ESBL E. coli) in Sungai Terengganu, Malaysia. *Malaysian Appl. Biol.* **53**(4), 65–75 (2024).
69. Wong, Y. J., Shimizu, Y., He, K. & Nik Sulaiman, N. M. Comparison among different ASEAN water quality indices for the assessment of the spatial variation of surface water quality in the Selangor river basin Malaysia. *Environ. Monitoring Assess.* **192**(10), 644 (2020).
70. Gelsey, K., Chang, H. & Ramirez, D. Effects of landscape characteristics, anthropogenic factors, and seasonality on water quality in Portland Oregon. *Environ. Monitoring Assess.* **195**(1), 219 (2023).
71. Kim, H., Foster, E. & Chang, H. Transition of water quality policies in Oregon, USA and South Korea: a historical socio-hydrological approach. *Hydrol. Sci. J.* **66**(15), 2117–2131 (2021).
72. Cude, C. G. Oregon water quality index a tool for evaluating water quality management effectiveness 1. JAWRA Journal of the American Water Resources Association, **37**(1), 125-137 (2001).
73. Yang, S., Zhou, L., Zhang, P., Fang, S. & Li, W. Evaluating the spillover value of ecological products from urban rivers eco-restoration: A quasi-natural experiment in Wuhan China. *Ecol. Indic.* **156**, 111095 (2023).
74. Das, A. Surface water quality evaluation of Mahanadi and its Tributary Katha Jodi River, Cuttack District, Odisha, using WQI, PLSR, SRI, and geospatial techniques. *Appl. Water Sci.* **15**(2), 26 (2025).
75. Khan, I. & Umar, R. Machine Learning-driven optimization of water quality index: a synergistic entropy-critic approach using spatio-temporal data. *Earth Syst. Environ.* **8**(4), 1453–1475 (2024).
76. Wang, X., Li, Y., Qiao, Q., Tavares, A. & Liang, Y. Water quality prediction based on machine learning and comprehensive weighting methods. *Entropy* **25**(8), 1186 (2023).
77. Chaudhary, S., Singh, G., Gupta, D., Singh Maunas, S. & Mishra, V. K. Characterization of groundwater potability and irrigation potential in Uttar Pradesh, India using water quality index and multivariate statistics. *J. Hydro Inform.* **26**(5), 1100–1121 (2024).
78. Gad, M. et al. New approach to predict wastewater quality for irrigation utilizing integrated indexical approaches and hyperspectral reflectance measurements supported with multivariate analysis. *Sci. Rep.* **15**(1), 16395 (2025).
79. Valentini, M., dos Santos, G. B. & Muller Vieira, B. Multiple linear regression analysis (MLR) applied for modelling a new WQI equation for monitoring the water quality of Mirim Lagoon, in the state of Rio Grande do Sul—Brazil. *SN Appl. Sci.* **3**(1), 70 (2021).
80. Luan, S. et al. High resolution water quality dataset of chinese lakes and reservoirs from 2000 to 2023. *Sci. Data* **12**(1), 572 (2025).
81. Das, A. Prediction of urban surface water quality scenarios using water quality index (WQI), multivariate techniques, and machine learning (ML) models in water resources, in Baitarani River Basin, Odisha: potential benefits and associated challenges. Earth Systems and Environment 1-37. (2025b)
82. Paikaray, S. et al. Impact of urban waste water effluents on ionic and trace metal behavior of Sutlej River water around Central Punjab India. *Toxicol. Environ. Chem.* **107**(4), 515–534 (2025).
83. Kouadri, S., Pande, C. B., Panneerselvam, B., Moharir, K. N. & Elbeltagi, A. Prediction of irrigation groundwater quality parameters using ANN, LSTM, and MLR models. *Environ. Sci. Pollut. Res.* **29**(14), 21067–21091 (2022).
84. Hasan, M. S., Ahmed, S. S., Uddin, M. N., Begum, M. & Rahman, M. O. Deciphering morphometric relationships of anacardiaceae (R. BR.) Lindl. In Bangladesh. *Bangladesh J. Bot.* **54**(2), 199–209 (2025).
85. Benkov, I., Varbanov, M., Venelinov, T. & Tsakovski, S. Principal component analysis and the water quality index—A powerful tool for surface water quality assessment: a case study on Struma River Catchment Bulgaria. *Water* **15**(10), 1961 (2023).
86. Shrestha, A., Shrestha, S. M. & Pradhan, A. M. S. Assessment of spring water quality of Khandbari Municipality in Sankhuwasabha District, Eastern Nepal. *Environ. Sci. Pollut. Res.* **30**(43), 98452–98469 (2023).
87. Das, A. Surface water quality evaluation impacting drinking water sources and sanitation using water quality index, multivariate techniques, and interpretable machine learning models in Mahanadi River, Odisha (India). *Environ. Geochem. Health* **47**(11), 497 (2025).
88. Zafar, M. M. & Kumari, A. Spatiotemporal evaluation of the impact of anthropogenic stressors on physicochemical characteristics and water quality of the River Ganga using GIS-based approach in the middle Gangetic Plains at Patna, Bihar India. *Water Sci. Technol.* **89**(5), 1382–1400 (2024).
89. Malik, Z., Mirani, A., Nagaraj, S. & Ravindiran, G. Assessment of groundwater suitability for drinking and irrigation purposes using water quality index, seawater mixing index, human health risk assessment, and irrigation suitability indices. *J. Water Chem. Technol.* **47**(4), 390–403 (2025).
90. Sabinaya, S. et al. Multi-model exploration of groundwater quality and potential health risk assessment in Jajpur district Eastern India. *Environ. Geochem. Health* **46**(2), 57 (2024).
91. Karunanidhi, D., Aravinthasamy, P., Jayasena, H. C., Subramani, T. & Adimalla, N. Groundwater quality estimation for drinking and irrigation suitability in a drought-prone region of south India with health hazard computation and spatial analysis using GIS. *Environ. Earth Sci.* **84**(17), 503 (2025).
92. Das, A. Water quality assessment and geospatial techniques for the delineation of surface water potential zones: a data-driven approach using machine learning models. Desalination and Water Treatment, 101461. (2025d)
93. Elfeky, A. M., Alfaisal, F. M. & El-Shafei, A. Analyzing riyadh treated wastewater parameters for irrigation suitability through multivariate statistical analysis and water quality indices. *Water* **17**(5), 709 (2025).
94. Abadi, H. T., Alemayehu, T. & Berhe, B. A. Assessing the suitability of water for irrigation purposes using irrigation water quality indices in the Irob catchment, Tigray Northern Ethiopia. *Water Qual. Res. J.* **60**(1), 177–195 (2025).
95. Mahananda, M. R., Mohanty, B. P., & Sahu, R. R. Risk Assessment of Heavy Metals from the Ib and Bheden Rivers: The main tributaries of Mahanadi in Western Odisha, India. In Mahanadi River: the environmental challenges and way forward pp. 147-164 Singapore: Springer Nature Singapore. (2025)
96. Mishra, S., Kumar, A. & Shukla, P. Estimation of heavy metal contamination in the Hindon River, India: an environmetric approach. *Appl. Water Sci.* **11**(1), 2 (2021).

97. Gogoi, P. et al. An integrative water quality index and multivariate modeling approach to assess surface water quality, trophic status and nutrient source apportionment in a large tropical reservoir, Hirakud–the longest earthen dam in Asia. *Appl. Water Sci.* **15**(8), 1–2 (2025).
98. Barik, P. & Biswal, T. Holistic approach towards pollution abatement of groundwater in major industrial belts of Jharsuguda District, Odisha, India and its modelling. *Water Environ. Res.* **97**(6), e70086 (2025).
99. Das, A. A Comprehensive analysis, hydrogeochemical characterization and processes controlling surface water quality: entropy-based WQI, geospatial assessment, PIS, NPI, and multivariate approaches in Mahanadi Basin, Odisha (India). Water-Energy Nexus. (2025e)
100. Das, A. (2025f). Applying the water quality indices, geographical information system, and advanced decision-making techniques to assess the suitability of surface water for drinking purposes in Brahmani River Basin (BRB), Odisha. Environmental Science and Pollution Research, 1-36.
101. Eid, M. H. et al. Monte Carlo simulation and PMF model for assessing human health risks associated with heavy metals in groundwater: a case study of the Nubian aquifer Siwa depression Egypt. *Front. Earth Sci.* **12**, 1431635 (2024).
102. Zhang, W., Li, S., Zhao, K., Chai, J., Wan, B., Qin, Y., & Baloch, M. Y. J. E. coli phage transport in porous media: response to colloid types and water saturation. *Science Of The Total Environment*, *906*, 167635 (2024)
103. Eid, M. H., Pinjung, Z., Mikita, V., Bence, C., & Szűcs, P. A novel integration of self-organizing maps and NETPATH inverse modeling to trace uranium and toxic metal contamination risks in West Mecsek, Hungary. Journal of Hazardous Materials 139291. (2025)
104. Mukut, S., Rahaman, M. M., Azim, M. R., Hossain, M. M. & Uddin, M. H. Water quality assessment of Karnaphuli River of Bangladesh using CCME-WQI method. *Asian J. Environ. Ecol* **20**(1), 6–15 (2023).
105. Chowdhury, R. M., Ankon, A. A. & Bhuiyan, M. K. Water Quality Index (WQI) of Shitalakshya River near Haripur power station, Narayanganj Bangladesh. *J. Eng. Sci.* **12**(3), 45–55 (2021).
106. Uddin, M. G., Nash, S. & Olbert, A. I. A review of water quality index models and their use for assessing surface water quality. *Ecol. Indic.* **122**, 107218 (2021).
107. Hasan, M. M., Ahmed, M. S., Adnan, R. & Shafiquzzaman, M. Water quality indices to assess the spatiotemporal variations of Dhaleshwari river in central Bangladesh. *Environ. Sustain. Indic.* **8**, 100068 (2020).
108. Tahmina, B. et al. Assessment of surface water quality of the Turag River in Bangladesh. *Res. J. Chem. Environ.* **22**(2), 49–56 (2018).
109. Muyen, Z., Rashedujjaman, M. & Rahman, M. S. Assessment of water quality index: a case study in Old Brahmaputra river of Mymensingh District in Bangladesh. *Progress. Agric.* **27**(3), 355–361 (2016).
110. Nath, R. K. et al. Assessment of heavy metal concentration in the water of major carp breeding River Halda Bangladesh. *Sustain. Chem. One World* **3**, 100018 (2024).
111. Zhang, W. et al. Health risk assessment during in situ remediation of Cr (VI)-contaminated groundwater by permeable reactive barriers: a field-scale study. *Int. J. Environ. Res. Public Health* **19**(20), 13079 (2022).
112. Li, S. et al. Migration risk of Escherichia coli O157: H7 in unsaturated porous media in response to different colloid types and compositions. *Environ. Pollut.* **323**, 121282 (2023).

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Author contributions

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Declarations

Competing interest

The author declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Additional information

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