Environmental and Sustainability Indicators 18 (2023) 100247

Contents lists available at ScienceDirect

Environmental and Sustainability Indicators

journal homepage: www.sciencedirect.com/journal/environmental-and-sustainability-indicators

Surface water quality profiling using the water quality index, pollution index and statistical methods: A critical review

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ARTICLE INFO

Keywords:
Pollution index (PI)
Surface water quality
Water pollution assessment
Water quality monitoring
Water quality parameters
Water quality index (WQI)
Water quality management system

ABSTRACT

Surface water is heavily exposed to contamination as this is the ubiquitous source for most of the water needs. This situation is exaggerated by the excessive population, heavy industrialization, rapid urbanization, and improper sanitation. Comprehensive measurement and knowledge extraction of surface water quality is therefore pivotal for ensuring safe and hygienic water use. Consequently, surface water quality profiling has received remarkable academic attention in recent decades that produces an ample amount of research results. This study, therefore, conducts a comprehensive systematic literature review to summarize and structure the existing literature and to identify current research trends and hotspots. Reported results suggest that the terrain of fresh surface water includes 13 distinct water sources that are predominantly used in 5 sectors. These sectors often cause the water pollution in the form of industrial effluents, agricultural runoffs, and domestic sewage. For profiling the water quality, around 23 Water Quality Index (WQI) models, and 10 Pollution Index (PI) models are used in research. These models often use several water quality parameters. This study reports an exhaustive taxonomy of 69 prominent quality parameters in three categories which will support their adoption for these models. Finally, the limitations of the current manual water quality measurement approaches are summarized to propose a set of seven requirements for the tech-intensive water quality profiling research and system development.

1. Introduction

Surface water refers to anybody of liquid water found on the Earth's surface. This includes, the ocean water and the water deposited in the inland repositories, e.g., rivers, streams, lakes, wetlands, reservoirs and creeks (Dooge 2009). Liquid surface water accounts for more than 97% of the Earth's hydrosphere within which 96% is saltwater in the ocean and only 1.1% is the fresh liquid water (Dooge 2009; Ball 2015). Of this 1.1% fresh water, 99% is groundwater and only 1% is the fresh surface water (Dooge 2009; Berner and Berner 1996). Nonetheless, fresh surface water is one of the most indispensable natural elements in shaping the environment and maintaining various forms of life on this planet (Ahmed 2016). Fresh water is fundamental for all living organisms, to human health, to food production and to most industrial processes (Ahmed 2016; Nguyen and Huynh 2022). With rapid urbanization, industrialization and agricultural production, the fresh surface water is becoming even more pivotal than ever before for the sustainability of human civilization (Ahmed 2016). Surface water is therefore the ubiquitous source for the majority of water needs, including drinking and domestic purposes, industrial and research activities, irrigation and agricultural production, horticulture, livestock farming and aquatic life management including fish and fisheries (Ahmed 2016; Behmel et al. 2016).

However, with the rapid proliferation of population and socio-economic development, the use and scarcity of this limited fresh surface water are increasing hastily (Dooge 2009; Najafi Saleh and AuthorAnonymous, 2020). A natural consequence of this is the deteriorating water quality due to heavy exposure to contamination and pollution (Ahmed 2016). This pollution can be due to both the natural and human-related activities (Uddin et al., 2021). Natural factors that influence water quality are hydrological, atmospheric, climatic, topographical and lithological (Magesh et al. 2013; Mahmood 2018). Human

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https://doi.org/10.1016/j.indic.2023.100247
Received 18 January 2023; Received in revised form 6 March 2023; Accepted 17 March 2023
Available online 22 March 2023

activities that adversely affect water quality are mining, livestock farming, production and disposal of effluent water (e.g., industrial, municipal and agricultural), increased sediment run-off or soil erosion due to land-use change and heavy metal pollution (Yousefi et al., 2018; Lobato et al. 2015; Sánchez et al. 2007). Colossal contamination and pollution vary based on the establishment and its' water usage pattern (Yousefi et al., 2018). For instance, water bodies close to the heavy industrial zone are highly susceptible to heavy metals and hazardous substances that are discharged as a by-product of the production process. The wetlands and water sources surrounding the agricultural lands are exposed to fertilizers and residue of pesticides (e.g., organophosphate, carbamate and organochlorine groups) (Chowdhury, Banik, Uddin, Moniruzzaman, Karim and Gan 2012b; Syeed et al., 2020). According to the statistics, one-quarter of the earth's population has no access to the safe water supply and one-half of the world's population has no access to adequate sanitary facilities (Dooge 2009; Ball 2015). This adversary leads to the widespread of water-related diseases, claiming over 5 million deaths per year (Dooge 2009). Therefore, persistent monitoring and control of the quality for fresh surface water is considered as a top priority for all the countries in the world (Ly and Larsen, 2015; Behmel et al., 2016). Monitoring water quality helps countries to assess, predict and control the water pollution and provides an evidential means for planning the sustainable use of the water resources (Turner et al., 2009; Firoz 2007; Mama et al. 2021). However, in the recent times, developing countries have faced significant problems in preserving the water quality when trying to improve water supply and sanitation (Mama et al., 2021; Carvalho et al., 2011; Debels et al. 2005). Even developed countries are facing challenges to sustain their water quality due to nutrient enrichment and eutrophication issues (Ortega et al. 2016; Pham et al. 2022).

Since water is the key factor for the sustainability of human civilization and the earth's environment, researchers have carried out extensive research in favor of the maintenance and management of the fresh surface water quality (Dooge 2009; Uddin et al., 2021). Consequently, plenty of research was conducted in the last two decades for profiling the water quality to understand the overall health of an ecosystem and the condition of the surface water (Drasovean and Murariu 2021). Other research works evaluated the water quality by leveraging distinct Water Quality Index (WQI) models (Uddin et al., 2021; Lumb et al., 2011), Pollution Index (PI) models (Kurnaz et al., 2016; Kumar et al., 2019) and Statistical methods for periodic assessments and time-series analysis (Nguyen and Huynh 2022; Balla et al. 2022; Schreiber et al. 2022). These models and methods were populated with several water quality parameters that signify distinct characteristics of the water body (Yousefi et al. 2017; Schreiber et al., 2022; Parmar and Bhardwaj 2014). Along this direction, research works were also targeting tech-intensive system design and development for remote sensing, measurement and monitoring of the surface water quality (Drasovean and Murariu 2021; Islam et al., 2020).

Largely, this plethora of research have produced significant results that require a systematic synthesis for an in-depth comprehension of the surface water quality monitoring and management for practical use. In this research, an exhaustive systematic literature survey aka *SLR* has been conducted to summarize and structure the existing body of knowledge on the concerned domain (Kitchenham et al. 2010). The objective and thus the contribution of this study is to (a) draw the holistic landscape of the fresh surface water, their usage pattern and source of pollution, (b) derive a three-dimensional classification of the water quality parameters pertaining to their natural and indicative properties and the usage of water, (c) develop encyclopedic documentation of the water quality assessment models and statistical methods in relation to the parameters, water sources, usage pattern and model performance and finally, (d) shed light on the future research concerning model performance and tech-intensive water quality profiling.

Reported results suggest that the terrain of fresh surface water includes 13 distinct water sources that are predominantly used in 5 sectors. These sectors often cause the water pollution in the form of industrial effluents, agricultural runoffs, and domestic sewage, among others. There are 23 Water Quality Index (WQI) models, and 10 Pollution Index (PI) models that are used in research for water quality assessment and pollution measurement. Alongside, several statistical methods are applied for predictive analysis of the water quality. All these models follow a four-step evaluation process for the water quality measurement, that includes, selection of appropriate set of quality parameters, determining parameter sub-indices, and assigning relative weights to the parameters, and finally, applying an aggregation function to compute the water quality or pollution index. However, eclipsing problem and model uncertainty often lead to inconsistent and inaccurate measurement for the models. Alongside, the selection of parameters for a specific WQI and PI model is influenced by three critical factors, e.g., the natural properties of the parameters, the purpose for which the water is to be used, and the environmental significance of a water quality parameter and the extent to which quality is to be ensured. This study therefore developed an exhaustive taxonomy of 69 water quality parameters in these three categories that can be adopted for the models. Finally, the limitations and lack of practical usability of the current manual water quality measurement approaches are summarized to proposes a set of seven requirements for the tech-intensive water quality profiling research and system development. To the best of our knowledge this is the first comprehensive review on the topic that binds together all necessary perspectives of the water quality assessment for an overarching understanding.

This paper is organized as follows, in Section 2 the research rationale in relation to the objectives and related research is presented, Section 3 details the manifestation of the SLR research method for this study. Exclusive findings and observations are categorically reported in Sections 4, 5 and 6. Section 7 details the recommendation and future research work. Finally, the validation arguments of the study and concluding remarks are drawn in Section 8 and 9, respectively.

2. Research rationale

Since the water quality measurement research has become prevalent, there is a need to analyze the existing literature for revealing the domain's intellectual structure and to identify the critical research gaps (Akter et al. 2016; Bartram et al., 2001; Bo et al. 2022). There have been a few systematic literature reviews on the related topic to date that investigate the WQI and PI models, their applications, and performance. For example, in (Uddin et al., 2021) a comparative discussion on the most prominent WQI models, their structure, the process of parameterization and model conceptualization is presented. Furthermore, the issues concerning model performance and future research directions are highlighted. Similar investigation is conducted in (Lumb et al., 2011; Poonam et al., 2013) and (Patil et al., 2012). Other studies have reviewed different methods (e.g., Hyperion, WQI and PI) in measuring the lake water quality, and recommend that the combination of pollution prevention, water re-use and recycling approach would be effective for the quality assurance (Schreiber et al., 2022; Bhateria and Jain 2016). Alongside, the impact of physio-chemical parameters in determining the surface water quality is discussed in (Patil et al., 2012). Few of the studies reviewed the applicability of PI models and their effectiveness in measuring heavy metal (HM) and metalloid Pollution (Karami et al., 2012; Sarkar et al., 2019; Prathumratana et al., 2008; Islam et al. 2018; Hasan et al., 2019; Parvin et al., 2022). Finally, review on the suitability of AI and ML based models in evaluating surface water quality were conducted in (Lowe et al., 2022; Chen et al. 2020) and (Altalak, Ammad uddin, Alajmi and Rizg 2022). The findings suggest that the ANFIS and ANN models perform the best in predicting the water quality.

Although these reviews yield new and important insights, they are mostly confined within a narrow domain of surface water quality measurement and do not attempt to identify the most influential contributions over a longer time frame. These studies fall short of portraying an overarching comprehension of the surface water quality monitoring process that connects all the required perspectives, e.g., an in-depth understanding of the water sources in relation to their usage and pollution pattern, providing a detailed taxonomy of the quality assessment parameters and associated models in determining their influence and contribution with respect to the water source, water use, geo-location and pollution. As a result, it is necessary to review the literature to reveal the current research foci, trends and hotspots to have a comprehensive understanding of the surface water quality measurement, monitoring and management process.

To fill the knowledge gap, this study leveraged the bibliographic literature review method for a rigorous quantitative and qualitative analysis of the reported research at the intersection of surface water landscape, water quality parameters and quality assessment approaches (e.g., methods, models and technologies) (Wanyama et al., 2022). It is argued that this study made several contributions to the existing literature by examining the fresh surface water sources to define their usage pattern and the instigation of pollution. Then, provides a three-dimensional classification of the quality parameters pertaining to their natural and indicative properties and the usage of water in determining the water quality. Then, develops an encyclopedic documentation of the water quality assessment models (e.g., WQI and PI models) and statistical methods in relation to the parameters, water sources, their usage pattern, and model performance. Finally, the gaps in current research are documented through an exclusive culmination of the reported results to suggest areas for further investigation. Two potential research directions are detailed, namely, the requirements for the design and development of a tech-savvy surface water quality profiling systems and the amelioration of the WQI and PI models in relation to their performance and applicability. For fine-grained assessment and investigation, a set of research questions analogous to these objectives are defined. Table 1 and Section 3.1 detail these research questions.

3. Methodology

Evidence-based research relies on the aggregation of the best instances of prior research for evaluating and interpreting all available research results relevant to a particular research question, or topic area, or phenomenon of interest (Syeed et al., 2013; Robinson et al., 2021; Kitchenham et al., 2010; Kitchenham and Charters, 2007). A prevalent research methodology for such research is the Systematic Literature Review, predominantly abbreviated as *SLR* (Syeed et al., 2013; Keele et al., 2007; Kitchenham 2004). Conducting a SLR involves several discrete activities that should be adequately defined and must be accomplished in an orderly manner for a through, impartial and fair synthesis of the existing research (Kitchenham et al., 2010; Kitchenham 2004). In SLR, it is also possible to deploy meta-analytic techniques to detect real cause and effects in the research for drawing valid conclusions, which is otherwise, left unnoticed (Kitchenham and Charters, 2007; Petticrew and Roberts 2008). Following the guidelines for conducting a comprehensive SLR (Robinson et al., 2021; Syeed et al., 2013; Kitchenham and Charters, 2007; Keele et al., 2007), this study adopted the review process sketched in Fig. 1. This process is detailed in the subsequent sections.

3.1. The review objectives and the research questions

The starting point of a review is to define a set of explicit research objectives, which is already reported in Section 2. The next step is to bind these objectives against a set of research questions (RQs) for fine grained assessment of the review articles. Table 1 defines the research questions and their mapping with the objectives that they address.

Table 1
Study research questions and objectives.

Research Question	Addressed In	Objective
[RQ1.] What is the landscape of the fresh surface water in relation to their sources, intended usage and the origin of contamination?	Section 4	To draw a holistic categorization of the fresh surface water in order to comprehend the relationship among the water sources, their usage and pollution pattern.
[RQ2.] What taxonomy of water quality parameters can be derived in relation to their natural factors (e.g., physical, chemical and biological properties)?	Section 5.1	To develop an exhaustive three-dimensional classification of the water quality parameters pertaining their usage or influence in measuring the water quality.
[RQ3.] What taxonomy of water quality parameters can be derived for measuring water quality from the perspective of its' intended use?	Section 5.2	
[RQ4.] What taxonomy of water quality parameters can be derived in relation to their specific quality indicative properties?	Section 5.3	
[RQ5.] What are the Water Quality Index (WQI) models and PI Models used to measure the water quality?	Section 6.1 Section 6.2	To materialize the taxonomy of water quality measurement models and associated statistical methods for monitoring the water quality both in spatial and temporal regional variations.
[RQ6.] What are the statistical methods explored for optimizing WQI model uncertainty, parameter variability and predictive time-series analysis of the water quality?	Section 6.3	
[RQ7.] What are the potential research directions that can be explored in relation to the methods, models and tech-intensive management of surface water quality?	Section 7	To shed light on the future research concerning the performance of the WQI models and PI models and derive the requirements for a tech intensive system with AI integrated geo-tagged intelligence for remote sensing, profiling and management of the surface water quality. The system should facilitate automatic assessment, predictive forecasting and derive factual observations to plan for sustainable management of water resources.

3.2. Article selection and quality assessment

The article selection process is intended to identify those primary studies (i.e., research articles) that provide direct evidence about the research questions (Kitchenham et al., 2010; Syeed et al., 2013). In order to ensure the comprehensiveness of the collected articles and to reduce the likelihood of bias, a well-defined strategy should be adopted (Wanyama et al., 2022). Therefore, following the recommendations this study executed a five step process as defined below (Kitchenham et al., 2010; Wanyama et al., 2022).

3.2.1. Listing the digital libraries

The selection of appropriate digital libraries and associated search engines are pivotal for ensuring the authenticity of the articles (Kitchenham and Charters, 2007). This selection process is influenced by the reputation of the libraries, the scientific content they publish and the relevance to the objective of this research. At the end of this process, five libraries and one search engine are nominated, a list of which is presented in Table 2. While searching with keywords in each of these

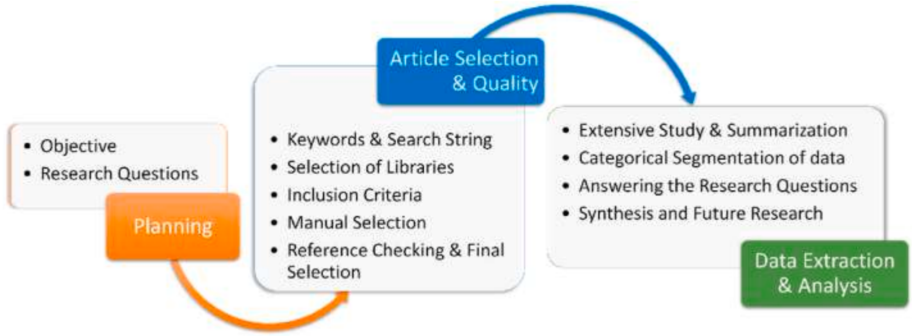


Fig. 1. Overview of the SLR methodology used in this research.

Table 2
Digital libraries.

Digital Libraries	Search Content	Search Duration
SpringerLink, ScienceDirect, IEEE, MDPI, ACM and Google Scholar?	Title, Keyword and Abstract of each Article	23 years range (1999–2022)

libraries, only the *title, keyword and abstract* of the papers are searched. This constraint increases the probability of shortlisting the most relevant articles (Kitchenham and Charters, 2007; Petticrew and Roberts 2008). The search period is kept between January 1999 and April 2022.

3.2.2. Keywords and search string

Automatic keyword search is the universally practiced approach to explore the digital libraries for collecting relevant articles (Kitchenham 2004; Beecham et al. 2008). Therefore, a broad automated keyword search is performed to get the initial set of articles. Knowing the fact that the construction of search strings varies among the digital libraries, this study first defines the search terms (i.e., the keywords) according to the research questions and the study objectives (Syeed et al., 2013). Then these keywords are combined to form the search string by consulting the guidelines of a specific digital library. The keywords and the generic search string are detailed in Table 3.

Table 3
Set of keywords and the generic search string.

Focus	Search Terms/Keywords	Generic Search String
Water Quality & Parameters	Synonyms Set-1 = “Water Quality” or “Surface Water Quality” or “fresh surface water” or “Water Quality Parameters” or “Water Quality profiling” or “Surface water Monitoring” or “Surface Water Management”.	Synonyms Set-1 AND Synonyms Set-2 AND
Methods & Models	Synonyms Set-2 = “Water Quality Models” or “Water Quality Index” or WQI or “Water Quality Indicator” or “Water Pollution” or “Pollution Index” or “Pollution Index Models” or “Statistical Methods” or “Statistical Technique”.	Synonyms Set-3 AND Synonyms Set-4
Surface Water Usage	Synonyms Set-3 = “Potable Water” or “Drinking Water” or Fisheries or Irrigation or “Industrial Use” or “Wastewater management” or “Conservative Use” or Agriculture or Undertaking or Ecological or “Aquatic Inhibition”.	
Tools & Techniques	Synonyms Set-4 = “Remote Sensing” or AI or “Artificial Intelligence” or ML or “Machine Learning” or IoT or “Internet of Things” or “Geo Referencing” or GIS or “System Design” or Automation.	

3.2.3. Inclusion criteria

As reported in the literature, automated keyword search frequently delivers a deceptive list of articles due to several deficiencies (Kitchenham 2004; Cornelissen et al. 2009). This includes a lack of a consistent and standardized set of keywords for article classification and a poorly formulated abstract. Therefore, to ensure the quality and relevance of the selected articles, explicit inclusion criteria should be defined (Cornelissen et al., 2009), an embodiment of which is presented in Table 4. The suitability of the articles is determined against these criteria during the manual selection process.

3.2.4. Manual selection

As stated above, the articles identified through the automated search process might contain irrelevant ones, while some relevant articles might be missing. Therefore, a manual assessment is conducted to ensure the quality, relevance and completeness of the articles listed through automated keyword search (Kitchenham et al., 2010; Petticrew and Roberts 2008). To accomplish this, each of the articles is assessed against the inclusion criteria listed in Table 4. Only the title, keywords and abstract are assessed and in case of doubt, the conclusion is checked. However, this process is subject to reviewer bias and therefore, requires an impartial assessment by a domain expert external to the review team (Robinson et al., 2021). For this, a professor external to the university is approached and given the set of selected articles and the selection criteria for his expert review (Robinson et al., 2021; Cornelissen et al., 2009). Any disagreement is resolved through discussion.

3.2.5. Reference checking and final selection

Finally, to ensure the inclusion of other relevant but missing articles (if any), a non-recursive search through the references of the manually selected articles are carried out. This concludes the exhaustive search of articles that resulted in 127 articles, including 123 journals and 4

Table 4
Article inclusion criteria.

Selection Category	Definition
Subject Domain	The subject area of the articles must unveil a strong focus on the taxonomy of surface water, parameters, their usage and contamination patterns, detection and profiling of the same by leveraging tech-savvy cutting-edge tools, methods and models.
Forums	Articles published in referred journals and conferences are included for the review. Technical reports published by the designated authorities, e.g., WHO, Water Development Board (WDB)- Bangladesh, US Environment Protection Agency, Department of Environment (DoE) Bangladesh, Canada Water Agency etc. are used for reference. Like most SLRs, books are not considered for review.
Ranking/ Quality Indexing	For the Journal Q1, Q2, Q3 or Q4. For Conference CORE A, CORE B and CORE C. Articles should be indexed at least in the Web of Science (WoS) and/or SCOPUS.

conference papers. The categorical collection of the articles along the digital libraries are presented in Table 5, a complete list of which is recorded in the appendix (Table 9).

3.3. Data extraction and synthesis

In order to answer the research questions, each article is thoroughly studied and interpreted to extract the most appropriate results and discussions relevant to the questions. For ensuring the quality and to reduce the reviewer bias, two independent teams from the author list have performed this task in two phases (Kitchenham et al., 2010; Kitchenham and Charters, 2007). In the initial phase, the first three authors reviewed and recorded the relevant information against each research question, and in the later phase, the other three authors verified the collected data to validate the originality and completeness.

3.4. Demography of the collected articles

Demographic assessment on the collected articles are carried out in two axis, namely, (a) through the major primary publication channels and (b) in accordance with the intensity of the research progress with time. Fig. 2a exhibits the count of primary studies in the X-axis against the publication's channels and publication type (e.g., journal and conference) in the Y-axis. There are several prominent publication channels (i.e., digital libraries) that publish articles on the water quality research, with *Springer, ScienceDirect and IEEE* being the front runner. Of these collected articles, 123 articles (96.8%) are identified as journals, whereas 4 papers (3.2%) are published in the designated conferences. The identification of journal articles are significantly higher than that of the conferences. The probable reason might be the strict adherence to the quality assessment criteria dictated in Table 4 and the extensiveness of the reported results.

The selected articles are published over a span of 23 years, between 1999 and 2022. Fig. 2b presents a trend chart revealing the frequency of publications in every two years of intervals, starting from 1999. It can be observed that most of the articles are published in recent years starting from 2011 to 2012 (approx. 70%) and there is a growing tendency in research interest in terms of the number of publications. Additionally, this line curve is best fitted with the exponential trendline (as shown in Fig. 2b) that affirm the rise in number of publications and research interest over the years.

4. The landscape of surface water sources, usage and pollution

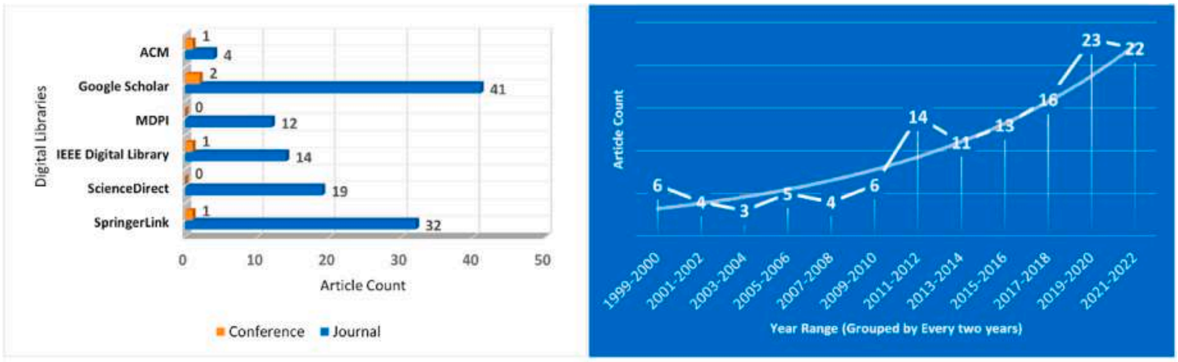
Surface water quality profiling is one of the high-priority mandates in almost all countries, especially in the developing world (Nguyen and Huynh 2022; Khan et al. 2021; Ustaoğlu et al. 2021). In line with this directive, several organizations, and research communities, worldwide, get affiliated with the process of measurement, monitoring and supervision of the surface water quality. The starting point of this process is to get a holistic understanding of the surface water with respect to their sources, intended use and the instigation of pollution (Karami et al., 2012; Prathumratana et al., 2008; Sarker et al., 2021). Consequently, the synopsis of the reviewed articles is drawn along this axis and is presented in Fig. 3.

Table 5
Statistics of the article selection process.

Digital Library	Automated Search	Manual Search	Reference Check	Total Articles
SpringerLink	92	26	7	33
ScienceDirect	65	16	3	19
IEEE Digital Library	36	14	1	15
MDPI	22	11	1	12
Google Scholar (Other)	101	39	4	43
ACM	19	5	0	5
Total	335	111	16	127

According to this figure, the terrain of surface water can be classified in 13 categories relative to the sources (Uddin et al., 2021; Bo et al., 2022; Sarker et al., 2021; Low et al. 2016; Zhao et al. 2013; Fallah and Zamani-Ahmadmahmoodi 2017). For example, rivers, wetlands, ponds, lakes, cascades, canals, wells, streams and others. Water extracted from these sources are primarily served in 5 sectors, as listed in the middle column of Fig. 3. Among these, the ***Agriculture sector*** generally covers the irrigation and animal husbandry (Acharya et al. 2020; Gholizadeh et al., 2016). Usually, untreated water from rivers, lakes, ponds and canals are used for irrigation (Low et al., 2016; Whitehead et al., 2009). For farm stock-drinking and wild-life watering purposes, water sources that are free from excessive dissolved salts, not too turbid, and are not contaminated/infested with chemical or biological pollutants, is suitable. The ***Industrial Complexes*** are heavily reliant on the rivers for their day-to-day operation (Sarker et al., 2021). Water from the river is well-harnessed for industrial production (e.g., for steel mills, paper mills, manufacturing factories and food processing), hydro-electricity generation and thermal power generation (Prathumratana et al., 2008; Karami et al., 2012; Sarkar et al., 2019). ***Domestic*** consumption of surface water includes drinking, and household usage, and most of the water sources are exploited for this purpose depending on their availability in each geographical location (Balla et al., 2022). However, use of these sources for human consumption requires great care in its' treatment and conditioning, especially water obtained from rivers and streams (Adimalla and Qian 2019; Chigor et al. 2012). ***Fisheries*** or pisciculture is the science and associated engineering process to produce fish and other aquatic resources for the purpose of providing human food (Amiri et al. 2021). This process often adopts or build custom canals, ponds, reservoirs, or lakes to provide ideal environment for fish culture (Low et al., 2016). For instance, in Manitoba, Canada, the lake Winnipeg and lake Manitoba are managed using quotas, mesh size of gill nets, seasonal regulation of fishing (Lumb et al., 2006; Amiri et al., 2021). On the other hand, in Bangladesh, inland closed water that constitutes 794,361ha of land in the form of ponds, seasonal cultured water body, lakes, Shrimp/Prawn farm and pen Culture, are allocated to produce approximately 2,060,408 tons of fish every year (Shamsuzzaman et al. 2017). The ***Undertaking*** defines a non-consumptive way of water usage in which the water is still available afterwards for other uses. For example, recreational use, food production and transportation of people and goods (Breen et al., 2018). From a water transport point of view, vessels of all kinds, of many different forms and makes, have navigated on rivers, streams and lakes throughout the ages and become the economically viable primary mode of freightage for businesses. For instance, in Ohio, USA, the Monongahela and Allegheny rivers are used to transport over sixty million tons of raw materials and finished products annually (Stickle, 1919).

Unfortunately, nearly all of these consumer sectors are the cardinal source of surface water contamination (Low et al., 2016; Karami et al., 2012; Prathumratana et al., 2008). For instance, most of the industrial complexes are built along the riverbanks that discharge industrial effluents directly into the rivers either without or partial treatment (D'Agostino et al., 2020; Sarker et al., 2021). Many a times, the magnitude of contamination is severe to the extent that it is becoming a serious threat to the environment, aquatic life and outbreak of waterborne diseases (e.g., cholera, diarrhoea, dysentery, hepatitis A) (Organization 2022). For reference, statistical evaluation on the physio-chemical properties of water in *Turag River*, Dhaka, Bangladesh reveals that Biochemical Oxygen Demand (*BOD*), Chemical Oxygen Demand (*COD)*, Electric Conductivity (*EC)*, Chlorine (*Cl-*), Dissolved Oxygen (*DO)*, *Turbidity*, and Total Dissolved Solids (*TDS)* are mainly responsible for the pollution, and are caused by the substantial amount of industrial effluent and toxicological compound discharge (Rahman et al., 2021). Alongside, the production of hydro-electric power impact



(a) Primary Article distribution along the digital libraries and the publication type

(b) Frequency of publications over a span of 23 years, between 1999 and 2022

Fig. 2. Demography of the primary articles.

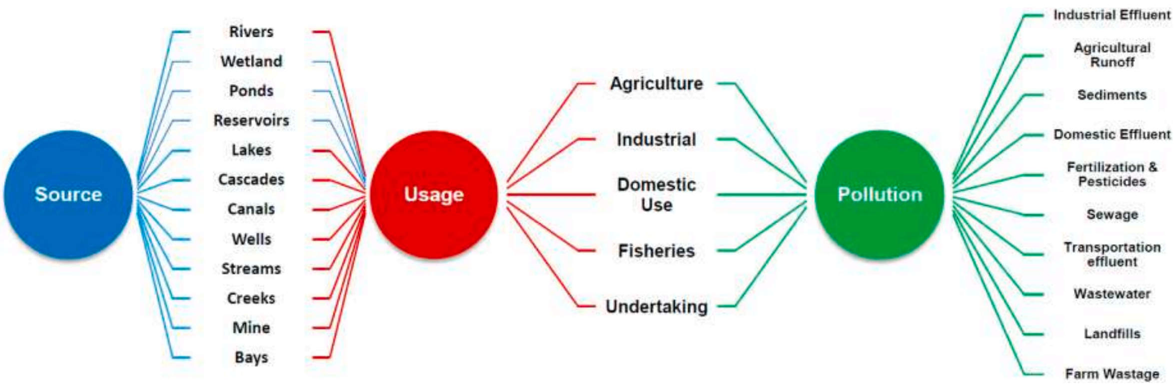
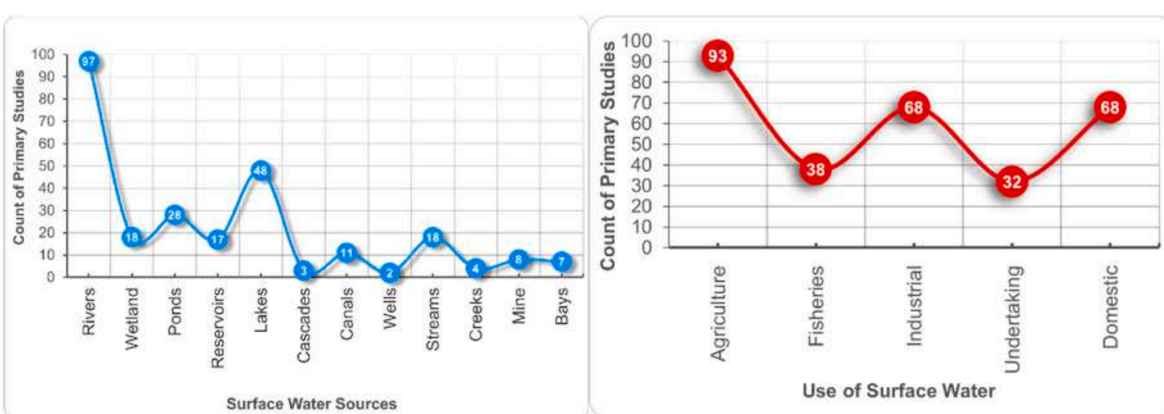


Fig. 3. Categorization of the surface water in terms of their sources, intended use and the instigation of pollution.

on the environment, particularly interrupts the spawning movements of fish in the dam (Roje-Bonacci and Bonacci 2013).

The agricultural runoffs, excessive and uncontrolled use of pesticides and fertilizers often get deposited in the nearby ponds, lakes and wetlands (de Souza et al., 2020). Often, heavy metals and pesticide residues are traced around the agricultural lands and vegetables in sewage-irrigated areas as well (Parvin et al., 2022; Islam et al., 2018). Consequently, aquatic organisms and fish species living in these water bodies are contaminated by the heavy metals (Kawser Ahmed, Baki, Kundu, Islam, Islam, Hossain et al., 2016; F. Islam et al., 2016). Alongside, having no or limited management for domestic effluent and sediments, these pollutants often contribute heavily to the pollution of the lake and river water (Gerecke et al. 2002).

Due to the causal relationship between the usage and the source of the surface water that leads to its' contamination, this study further categorizes the research articles along these dimensions. The intention is to better understand whether the reported research is analogous to the most frequently used sources and their management. The outcomes are plotted in Fig. 4a and b, where the earlier shows the frequency of articles that investigate a specific source of surface water, and the latter, lists the



(a) Source of Surface Water explored in the research

(b) Use of Surface Water studied in research

Fig. 4. Categorization of research articles.

frequency of articles that explore a particular usage type and pollution pattern. The findings confirm that river water is studied the most (in 74 articles), followed by the lakes (in 44 articles), reservoirs (in 17 articles), ponds (in 15 articles), and streams (in 12 articles). In relation to the usage of the water sources, it is noted that the agricultural, domestic, and industrial sectors are the dominating consumers, with article counts of 79, 67 and 53, respectively.

5. Water quality parameters and their classification

Management of surface water quality requires the collection and analysis of a large number of water quality parameters. A range of methods and tools have been developed to determine, measure, evaluate and synthesize these parameters for the water quality measurement (Uddin et al., 2021). Among these, the *Water Quality Index (WQI)* model is the highly appreciated one. This model is one of the 25 environmental performance indicators of the holistic Environmental Performance Index (EPI) (Boyacioglu 2010). This index offers a simple, concise and easy-to-understand method to express the quality of water bodies for varied water sources, usage and pollution. There are several *WQI* models that rely on aggregation functions to express water quality as a single number through the measurement and analysis of large temporally and spatially-varying water quality parameters (e.g., Dissolved Oxygen (*DO)*, Potential of Hydroge (pH), Nitrate ($NO3-$), Phosphate (PO_4^3-), Ammonia (*NH3)*, Chloride (CL^-), Hardness, Heavy Metals (*HM)*) (Uddin et al., 2021; Boyacioglu 2010).

The selection of water quality parameters is the most crucial step of the WQI measurement process (Uddin et al., 2021; Boyacioglu 2010). There are no less than 69 quality parameters to choose from, and their selection is often underpinned by several decisive factors, e.g., (a) the physical, chemical and biological characteristics of the water to be measured, (b) the purpose for which the water is to be used, (c) the extent to which the quality and purity to be ensured, (d) the environmental significance of a water quality parameter, and (e) the WQI model selected and the reasons for selecting it (Bartram and Ballance 1996; of European Communities 2000; Uddin et al., 2021; Boyacioglu 2010).

In this section a three-dimensional classification of the water quality parameters is derived. This classification is analogous to the first three factors presented above, namely, according to the natural properties (e.g., physical, chemical, and biological characteristics), based on the water usage pattern, and according to the water quality indicators.

5.1. Classification based on natural properties

Natural properties or factors of surface water define the characteristics of the water and its' suitability for a specific use, e.g., domestic,

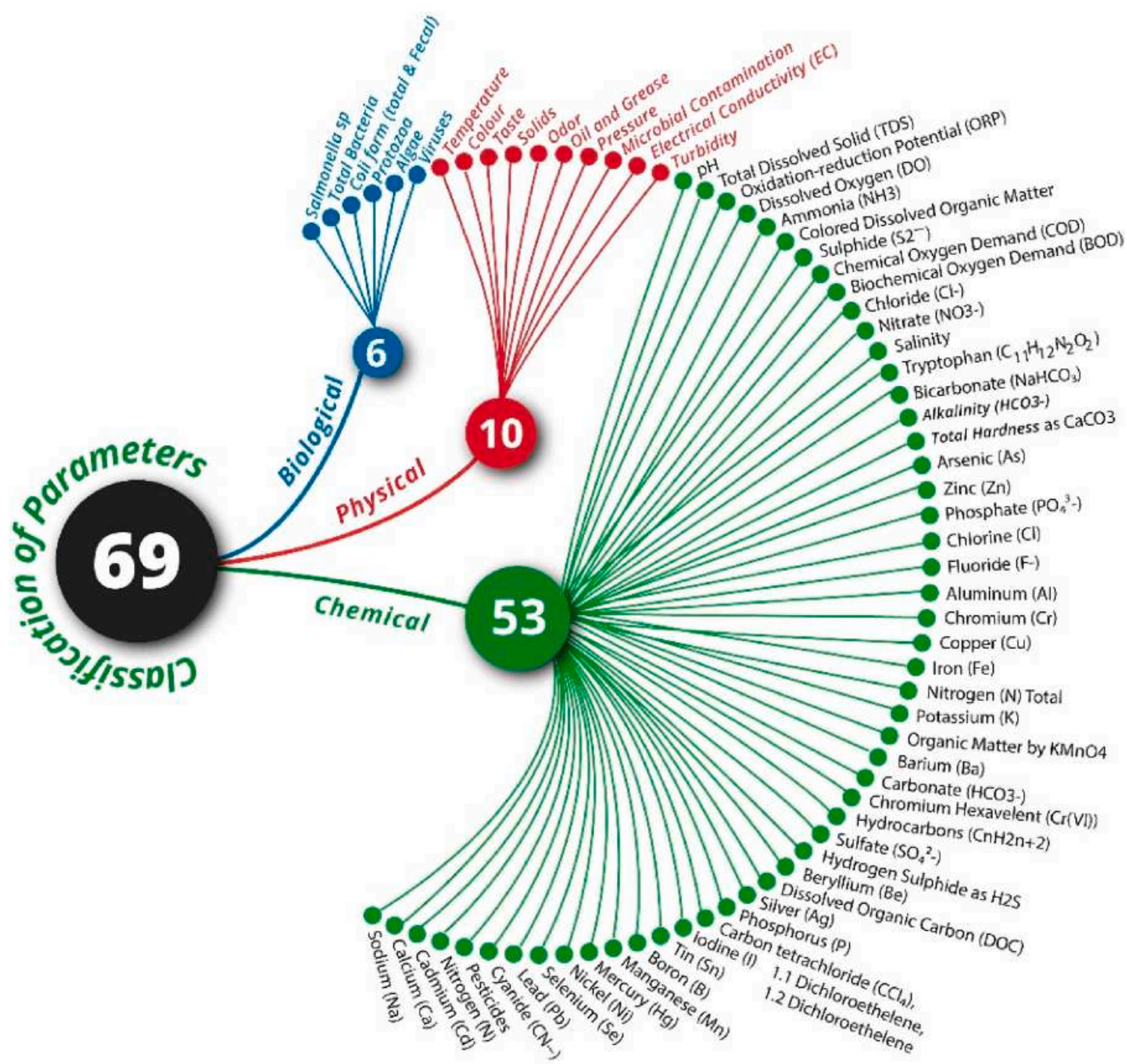


Fig. 5. Taxonomy of the 69 water quality parameters along their Natural factors, e.g., physical, chemical, biological and bacteriological.

agricultural, industrial, fisheries and others (Shamsuzzaman et al., 2017). There are approximately 69 distinct parameters that are directly associated with the quality assessment of the surface water and are being used by different Water Quality Index (WQI) and Pollution Index (PI) models. Depending on their natural properties, these 69 parameters can be classified along three categories, namely, *physical, chemical, and biological*. Measurement of the parameters along this taxonomy allow surface water to be assessed on its' specific quality aspect (Drasovean and Murariu 2021). For example, chemical and physical parameters are important in the rapid determination of the water quality, while biological parameters provide an exhaustive and complex analysis of the associated environment (Uddin et al., 2021; Drasovean and Murariu 2021). Fig. 5 demonstrates this taxonomy, where *6 parameters* are needed to characterize the biological properties, *10 parameters* are required to measure the physical properties, and *53 parameters* are needed to assess the chemical characteristics of surface water.

5.1.1. Physical parameters

Physical parameters of water signify the appearance and physical characteristics of the water. Referring to Fig. 5, there are 10 distinct parameters in this category, namely, *Temperature, Turbidity, Color, Taste, and Odor*, among others. These parameters can be observed and measured without changing the chemical composition of the substance (Gorde and Jadhav 2013a; Hussen et al. 2018). Imbalance in physical parameters often lead to impurities that are offensive to the sense of sight, taste, or smell, and make the water inappropriate for use (Omer 2019; Hussen et al., 2018). For example, *Turbidity* designates the presence of suspended materials such as clay, slit, finely divided organic material, plankton, and other inorganic materials in the water (Omer 2019). Low *Turbidity* water is clear, while high *Turbidity* water is cloudy or murky.

Temperature is an influential physical parameter that controls the palatability, viscosity, solubility, odors, and chemical reactions of the water (Omer 2019). For instance, water at a temperature between 10 and 15 °C is most palatable for human beings. Alongside, other bio-chemical process and properties of water, such as, the sedimentation and chlorination processes, the biosorption process of the dissolved heavy metals, and Biological Oxygen Demand (*BOD*) are affected by *Temperature* (Omer 2019; Arora 2017).

Other important physical parameters relating to the potability of water is the *Taste and Odor* (Omer 2019). Bad *Odor* and *Taste* are caused by the foreign substances (e.g., organic or inorganic materials, compounds, and dissolved gasses) that are often discharged by domestic, or agricultural sources (Lin et al., 2018). Finally, the *Electrical Conductivity (EC)* of water measures the *ion* concentration in the water body and defines its' suitability for irrigation and firefighting (Arora 2017; Omer 2019).

5.1.2. Chemical parameters

Water reacts with several chemical substances to change its' molecular structure and form a new compound substance (Beutler et al., 2014; Chormey et al. 2018). Consequently, there are several chemical parameters that play a pivotal role in defining the quality of surface water. This review identifies 53 chemical parameters as listed in Fig. 5, among which, the pH, *Alkalinity*, *DO*, *BOD*, Chlorine (*Cl*), Inorganic Toxic Substances, Fluoride ($F-$), Iron (*Fe*), Manganese (*Mn*), Copper (*Cu*), Nitrogen (*N2*) and Zinc (*Zn*), are the dominating ones (Omer 2019). The chemical characteristics of the surface water are affected by several sources, e.g., through soils and rocks with which thewater has been in contact, by agricultural and urban runoffs, wastewater dispatched by the municipal and industrial waste management system, or through microbial and chemical transformations (Hussen et al., 2018). Chemical contamination occurring through this process might cause severe health concerns (Akter et al., 2016).

One of the most important chemical parameters for water quality is the pH, which is a measure of how acidic/basic the water is (Arora 2017). Acidic water contains extra Hydrogen ions ($H+$), whereas basic water contains extra Hydroxyl ($OH-$) ions (Omer 2019). The pH values range from 0 to 14, within which a value less than 7 defines acidic water, a value of 7 defines pure water and a value greater than 7 indicates base solution (Beutler et al., 2014; Arora 2017). The *Alkalinity* of water is mainly caused by the presence of Hydroxide ions ($OH-$), Bicarbonate ions ($HCO\ ^{3}-$), and Carbonate ions (CO_3^2-), or a mixture of these two ions in the water. The high level of either acidity or alkalinity in water may be an indication of industrial or chemical pollution (Omer 2019).

Chloride ions ($Cl-$) occur naturally in the surface water and are usually not harmful to human health, except for causing an unpleasant salty taste if found in high concentration (Omer 2019). Alongside, relatively high Chloride concentration in freshwater (about 250 mg/L or more) may indicate pollution due to chloride-containing rock, agricultural runoff, and wastewater (Chatterjee 1996).

Nitrogen (*N2)* is the basic source of nutrients for water inhabitants, e. g., fish, and smaller organisms. The *Organic Nitrogen, Ammonia Nitrogen, Nitrite Nitrogen, and Nitrate Nitrogen* are the four forms of Nitrogen found in the water and wastewater (Beutler et al., 2014). Higher concentration of Organic and Ammonia nitrogen indicates water contamination due to sewage, whereas rapid growth of the algae that degrades the water quality is due to high concentration of Nitrate (Tchobanoglus, Burton and Stensel 2003). Additionally, drinking water having Nitrate concentration over 10 mg/L cause immediate and severe health risk for infants (Peavy et al., 1985).

Dissolved oxygen (DO) is a direct indicator of the surface water quality, and is therefore, one of the key parameters for measuring water pollution (Beutler et al., 2014). In general, the higher the concentration of *DO*, the better the water quality. Oxygen is slightly soluble in water and the actual amount varies depending on pressure, temperature, and salinity of the water (Tchobanoglus et al. 2003). *DO* has no direct effect on public health, but drinking water with very little or no oxygen tastes unpalatable to some people. However, fishes and other living organisms (e.g., bacteria, microorganisms) metabolize organic material through the consumption of *DO* (Beutler et al., 2014; Tchobanoglus et al. 2003). This process discharges CO_2 in the water and reduces the concentration of *DO*. Therefore, oxygen has to be continuously replaced by natural or artificial means in the water to maintain the level of *BOD*

Inorganic toxic substances (e.g., *Metallic* and *Nonmetallic* compounds) found in surface water even in trace amounts, pose severe health risks (Davis 2010). These substances often occur in water due to industrial discharges, and improper management of sediments and hazardous waste (Tchobanoglus et al. 2003). Among the metallic compounds, Arsenic (*As*) and Chromium ($Cr6+$) are the acute fatal poisons, and Cadmium (*Cd)*, Lead (*Pb)*, Mercury (*Hg)*, and Thallium (*T1)* may cause chronic diseases (DeZuane 1997; Campanella, Onor, D'Ulivo, Giannecchini, D'Orazio, Petrini and Bramanti 2016; Das, Dutta, Cervera and de la Guardia 2007; Lasheen et al., 1990; Organization et al., 1079 2020). Within nonmetallic compounds, Nitrates ($NO3-$) and Cyanides ($CN-$) cause chronic effects on the central nervous system and thyroid (Dojlido and Best, 1993).

Among other prominent chemical parameters for surface water, the $F-$ ions, *Fe*, *Mn*, *Cu* and *Zn* are nontoxic. These parameters are often beneficial for human health and for the growth of plants and animals, if found in permissible quantities (Beutler et al., 2014; Organization et al., 1996). For instance, a moderate amount of $F-$ ions in the drinking water is good for preventing tooth decay (Beutler et al., 2014; Peavy et al., 1985).

5.1.3. Biological parameters

Biological factors of water are measured by the presence of pollution indicators of organisms, e.g., *Total Germ* (e.g., Total Bacteria, Viruses, Salmonella spp.), *Coliforms* (both Fecal and Total), *Protozoa* and *Algae* (Wilhm and Dorris 1968; Holcomb and Stewart 2020). These are important parameters of water potability. The determination of biological quality follows a microbiological analytic procedure that analyses the samples of water and determines the concentration level (Barrell et al., 2000; Champa and Kabir 2018).

Bacteria are the single-celled plants that occur in three basic cell shapes and have rapid reproductivity (Beutler et al., 2014; Weibe 2021). Several life-threatening waterborne diseases, namely, typhoid and paratyphoid fever, leptospirosis, tularemia, shigellosis, and cholera are caused by bacteria (Peavy et al., 1985). A special group of bacteria is the *coliforms*, which is a very important biological and pollution indicator of surface water (Mara and Horan 2003). Due to their presence in the human intestinal system (e.g., pathogenic coliforms), they are often excreted with body wastes to water and sewage (Weibe 2021; Peavy et al., 1985). Coliform bacteria are aggressive organisms and survive in the water longer than most pathogens (Beutler et al., 2014; Weibe 2021).

The smallest biological structures are the *Viruses* that possess all genetic information necessary for their reproduction (Peavy et al., 1985). Many deadly diseases including infectious hepatitis and poliomyelitis are due to waterborne viral pathogens (Peavy et al., 1985; Organization et al., 1996; Weibe 2021). Finally, *Algae* are the microscopic plants with photosynthetic pigments (Weibe 2021; Mara and Horan 2003). They often create taste and odor problems for potable water and cause serious environmental and public health issues (Alley 2007; Viessman and Hammer 1993; Weibe 2021; Mara and Horan 2003).

5.2. Classification based on intended use

It is advised that measurement of the surface water quality should depend on the use of the water, the geo-location and the type of water (Murariu et al. 2019). Thus, potable water must not contain chemicals or micro-organisms which affect human health (Drasovean and Murariu

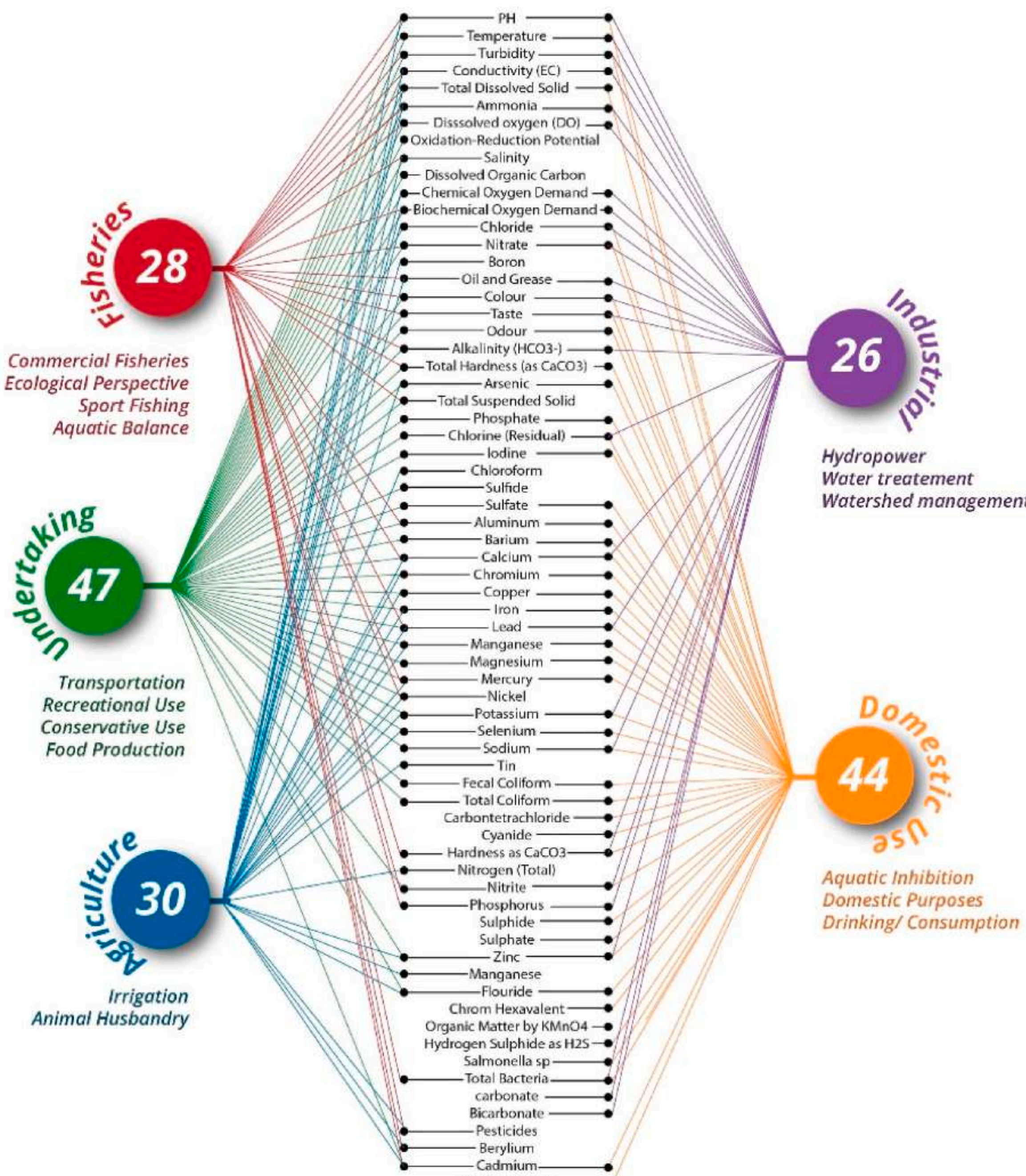


Fig. 6. A comprehensive classification of the 69 parameters along 5 fundamental usages of the surface water.

2021), whereas water used for agriculture/irrigation purposes should be free from large amount of sodium ions, high concentrations of nitrates and other contaminants (Drasovean and Murariu 2021; Bartram and Ballance 1996). The scientific community, therefore, recommends that a specific set of parameters should be selected that are subjected to assess the quality for a particular use of the water (Gorde and Jadhav 2013b; Murariu et al., 2019).

Consequently, this study carried out an in-depth classification of the 69 parameters along the five fundamental usages of the surface water (ref to Section 4 for the usage classification). A visual representation of this classification is presented in Fig. 6, where each of the parameters is mapped to one of the usage categories according to its' dominance. For example, the parameter pH influences all the usage categories, whereas *Coliform* only contributes to the quality measurement of the domestic and freshwater (undertaking). Additionally, this figure materializes the list of parameters required for an exhaustive assessment of the water quality in each usage category. For example, 28 parameters are needed for *Fisheries*, for *Agricultural* purposes 30 parameters should be exploited, 47 parameters are affiliated with the *undertaking* and assessment of 44 parameters can provide comprehensive analysis of the *domestic water*, and finally, 26 parameters can be evaluated for *Industrial Water* management.

However, in practice, only the basic set of parameters are evaluated by most of the WQI and PI models. This parameter set includes *Temperature*, *Turbidity*, pH, Suspended Solids (*SS*), Total Dissolved Solids (*TDS)*, Faecal Coliforms (*FC)*, Dissolved Oxygen (*DO)*, Biochemical Oxygen Demand (*BOD)* and Nitrate Nitrogen (*NH3–N)* (Omer 2019). Usually, the number of parameters varies between 4 and 26, depending on the WQI and PI model selected, or expert opinion on deciding the parameter significance, and above all, subject to the availability of data.

5.3. Classification based on indicative properties

Alongside the above categorization, other directives suggest that parameters should be classified based on the quality indicators that they pointed to. This classification supports the operational monitoring that is often based on the measurement of relevant biological, hydromorphological, physical and chemical properties of (European Communities 2000). Fig. 7 categorically list the parameters that contribute to the estimation of a specific quality indicator cited by the standard frameworks (Bartram and Ballance 1996). A pertinent discussion on this classification is presented below.

5.3.1. Basic parameters

Water quality parameters include physical, chemical and bacteriological properties, and they are measured based on the desired water usage and quality concern. However, according to the experts, there are 16 quality parameters, which can be considered as the basic set of indicators for ensuring water quality in general. Therefore, these parameters are often applied to the domestic, agriculture, industrial, fisheries and any other type of water quality measurement.

5.3.2. Toxic inorganic substances and persistent pollutant

To measure the toxicity and intensity of pollution, the inorganic substances and persistent pollutant need to be measured (Sarkar et al., 2019; Hasan et al., 2019). There are 19 parameters classified in metallic and nonmetallic categories that can be used for this purpose. Inorganic contaminants typically result from the leaching of a contaminated source zone into the surface water, such as waste disposal, industrial effluent disposals, and mine-tailing sites (Gerecke et al., 2002; Tchobanoglus et al. 2003). If these substances are found in the water even in trace amount, they can be a danger to public health (D'Agostino et al., 2020; Water and Organization, 2009).

The *Metallic compounds* include some toxic heavy metals, namely, Cadmium (*Cd)*, Chromium (*Cr)*, Lead (*Pb)*, Mercury (*Hg)*, Silver (*Ag)*, Arsenic (*As)*, Barium (*Ba)*, Thallium (*Tl)*, and Selenium (*Se)* (Tchobanoglus et al. 2003; Järup 2003). Their toxicity varies from being acute fatal poisons (e.g., *As* and *Cr6+*), to the source of chronic diseases (e.g., *Cd*, *Hg*, *Pb*, and *Tl*) (DeZuane 1997; Campanella et al., 2016; Das et al., 2007; Lasheen et al., 1990; Organization et al., 1079 2020). The concentration of these heavy metals can be determined by atomic absorption photometers, spectrophotometers, or inductively coupled plasma (ICP) for very low concentrations.

The *Nonmetallic compounds* includes Nitrates (*NO*3) and Cyanides

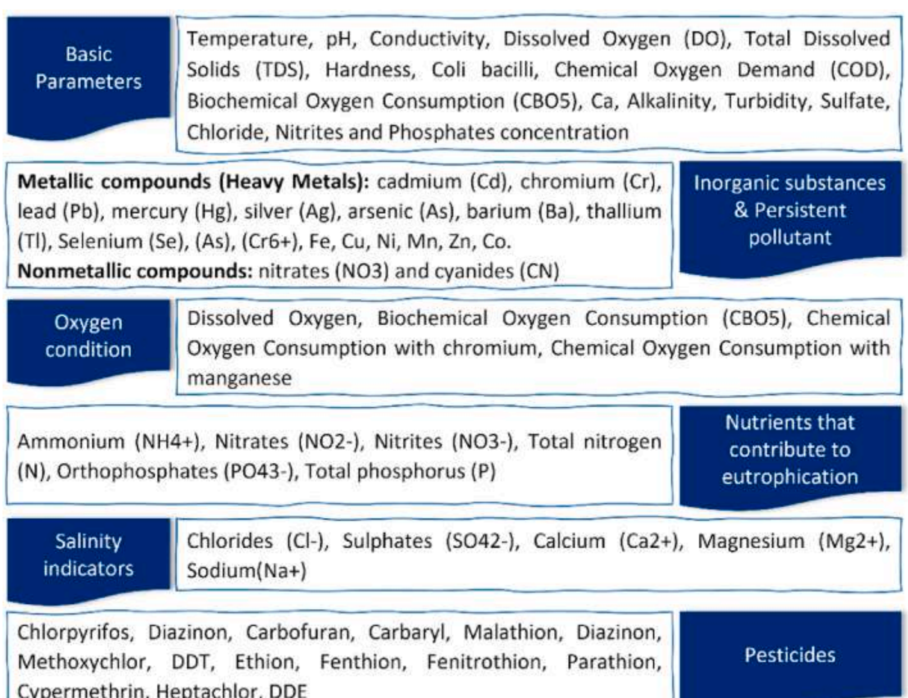


Fig. 7. Indicative classification of the water quality parameters.

(*CN*). Cyanide is a rapidly acting and potentially deadly chemical that causes oxygen deprivation by binding the hemoglobin sites and prevents the red blood cell from carrying the oxygen (Davis 2010). This causes a blue skin color syndrome called cyanosis. It also causes chronic effects on the central nervous system and thyroid (Dojlido and Best, 1993). Nonmetallic compounds can be measured by colorimetric, titrimetric, or electrometric methods (Beutler et al., 2014).

5.3.3. Oxygen condition

The measurement of Oxygen condition is an indicative measure that ensures the level of free oxygen present in the water (Rahman et al., 2021; Chapra et al., 2021). The categorical measurement of oxygen level can be evaluated with 4 parameters as listed in Fig. 7. This measurement is often crucial for the survival of fish and other aquatic organisms (Amiri et al., 2021).

5.3.4. Nutrients that contribute to eutrophication

Nutrients are chemical elements that the plants and animals need to grow and survive. Two of the most important and abundant nutrients are the *Nitrogen* and *phosphorus*. An overabundance of nutrients, primarily nitrogen and phosphorus in the water body is often harmful, as it starts a process called *eutrophication*. This process excels the algal blooms that turn the water green and block the sunlight. The decomposition of dead algae causes bacteria to consume the dissolved oxygen, creating *dead zones* for fish and other aquatic inhabitants (Pham et al., 2022).

5.3.5. Pesticides

Contamination of surface water due to pesticides (e.g., Chlorpyrifos, Diazinon, Carbofuran, Carbaryl, Malathion, Diazinon, Methoxychlor, DDT, and others) is caused by the persistent chemical erosion from the pesticide production factories, agricultural activities, or from the urban use (de Souza et al., 2020). Effects of pesticides on human health varies from mild to chronic, depending on the level of exposure to pesticides and age (Syafrudin et al. 2021). For instance, health effects may range from mild stinging eyes, rashes, nausea, dizziness to chronic effects, such as, cancers, birth defects, reproductive harm, and immunotoxicity (de Souza et al., 2020).

5.3.6. Salinity indicators

Salinity defines the dissolved salt content in a water body, identified by 5 distinct parameters, e.g., Chlorides ($Cl-$), Sulphates (SO_4^2-), Calcium (Ca^{2+}), Magnesium (Mg^{2+}), and Sodium ($Na+$). Salinity directly affects the agricultural production, water quality, ecological health of streams, terrestrial biodiversity, soil erosion, flood risk, and irrigation (Jóźwiakowska et al. 2020). For instance, with the increase in the concentration of $Cl-$ ions, the plants get poisoned and die. Also, a change in salinity affects the quality of water for irrigation and drinking (e.g., change in $Na+$ and $MgSO4$ causes laxative effect) (Jóźwiakowska et al., 2020).

6. On the quality assessment models and methods

Water quality profiling is an effective and economical way to understand the overall condition of the surface water and the health of an ecosystem (Drasovean and Murariu 2021). Profiling allows to monitor the surface water quality both in spatial and temporal regional variations (Gorde and Jadhav 2013b). This quality profiling is underpinned by the water usage pattern, water sources, geo-location, and the extent to which the quality and purity need to be measured (Balla et al., 2022). Considering these factors, several quality assessment models are proposed and put into practice (Schreiber et al., 2022; Parmar and Bhardwaj 2014). These models can be broadly classified along two axes, namely, the WQI models, and the PI models. Alongside the contemporary Statistical methods are also evaluated for predicting the changes in water quality in space and in time.

6.1. Water quality index (WQI) models

The *water quality index (WQI)* model produces a number as the indicator of water quality for a given location over time and are based on several water quality parameters that are supplied as input to the model (Drasovean and Murariu 2021). Therefore, the expression of a WQI model transforms a large number of complex water quality parameter measurements into an easy-to-comprehend information for people to understand and act upon (Drasovean and Murariu 2021; Drasovean and Murariu, 2021; Drasovean et al. 2018).

The use of such water quality indices for profiling the quality can be traced back to the mid-1800s (Abbasi and Abbasi 2012). However, WQI models have only been developed over the last 60 years with Horton proposing the first WQI model in the 1960s that uses 10 water quality parameters (Uddin et al., 2021; Poonam et al., 2013). His model proved significant for quality measurement for most of the waterbodies (Poonam et al., 2013). Later, Brown developed a rigorous version of Hortons' model, named NSF-WQI, with support from the National Sanitation Foundation (Noori et al. 2019). A panel of 142 water quality experts defined the process of parameter selection and weighting for this model (Abbasi and Abbasi 2012). Since then, several other WQI models have been developed and put into practice. Table 6 presents an exhaustive list of the WQI models that are currently in use, worldwide. In this table, a total of 23 WQI models are listed along with the executive summary of their primary properties, e.g., the list of parameters used, the origin and evaluation criteria, the water body where applied, and the reference for detail implementation of the models. In general, the structure of a WQI model consists of four main steps to be executed in sequence, namely, (a) selection of the water quality parameters, (b) produce the parameter sub-indices, (c) selection of weights for the parameters and finally, (d) use of an aggregation function to calculate the WQI (Abbasi and Abbasi 2012; Uddin et al., 2021; Poonam et al., 2013; Lumb et al., 2011; Gorde and Jadhav 2013a).

(Step 1) Select the water quality parameters:

The number of selected parameters for WQI models varies between 4 and 26, with most of the models waged 8 to 11 parameters (Ferreira et al., 2011; Lumb et al., 2006; Said et al., 2004; Lumb et al., 2011). As detailed in Section 5, parameter selection for a WQI model is often influenced by several factors. Such as, the geo-location, the physio-chemical properties of water to be evaluated, eutrophication, health concerns, oxygen availability, dissolved constituents, the intended use of the water, environmental significance and data availability (Debels et al., 2005). To assess these factors for the selection of appropriate number of parameters, the *Delphi Technique* is predominantly used for most of the WQI models (Abbasi and Abbasi 2012; Hsu and Sandford 2007). In this technique, interviews or surveys are conducted with the experts who, based on their experience suggest the appropriate set of parameters for a given water body to be assessed (House 1989). Apart from this approach, there is no other systematic technique developed to formalize and standardize the parameter selection process for general adoption. Additionally, the WQI models often do not consider the *hazardous parameters* and *toxic or radioactive constituents* to evaluate the water quality (Hernando et al. 2006; Parvin et al., 2022; Tripathee et al. 2016; Karami et al., 2012). The default list of parameters and their selection process for each WQI model is summarized in Column 3 of Table 6.

(Step 2) Produce parameter Sub-indices:

In this step, the measured values for the parameters are converted to dimensionless and unit less quantities, known as the parameter sub-indices (Abbasi and Abbasi 2012). There are several procedures available for calculating the sub-indices, namely, the *Parameter Concentrations* (Abbasi and Abbasi 2012), *Linear Interpolated Functions* (Noori

Table 6
Water Quality Index (WQI) Models for Spatial and Temporal Water quality profiling.

No	WQI Model Name	Parameters	Origin	Usage
1	Universal Water Quality Index (UWQI) (Banda and Kumarasamy 2020; Low et al., 2016)	13 Parameters: pH, Turbidity, NH3, Ca, Cl, Chl-a, EC, F, CaCO3, Mg, Mn, NO3, SO4. Parameter selection: Expert opinion and use.	South Africa. Additive version of different WQI's.	Rivers and other surface water reservoirs
2	(CCME) Canadian Council of Ministers of the Environment (Sharma and Kansal 2011; Uddin et al., 2017a; Balla et al., 2022)	Minimum 4 Parameters. (Any four). Parameter Selection: Delphi. Water Quality Levels: Excellent (95–100), Good (80–94), Fair (65–79), Marginal (45–65), Poor (0–44).	Canada. Modified version of BCWQI.	River, lakes, Wells and reservoir
3	Universal Water Quality Index (UWQI) (Banda and Kumarasamy 2020; Low et al., 2016)	13 Parameters: pH, Turbidity, NH3, Ca, Cl, Chl-a, EC, F, CaCO3, Mg, Mn, NO3, SO4. Parameter selection: Expert opinion and use.	South Africa. Additive version of different WQI's.	Rivers and other surface water reservoirs
4	Recreational water quality index (RWQI) (Breen et al., 2018; Poonam et al., 2013)	10 Parameters: pH, Turbidity, Detergents, NO3, COD, PO4, Total coliforms, Faecal coliforms, *Escherichia coli*, Enterococci. Technique Used: Delphi. Water Quality Levels: Excellent (91–100), Good (81–90), Medium (71–80), Poor (<70).	Argentina.	Recreational Water Source.
5	Weighted arithmetic Water Quality Index (WQI) (Akter et al., 2016; Ewaid and Abed 2017)	14 Parameters (any parameters). Parameter selection: Expert opinion and use. Water Quality Levels: Excellent (0–25), Good (26–50), Poor (51–75), Very Poor (76–100), Unsuitable for drinking (>100).	USA. Modified version of Horton and NSF Index.	Drinking Water Source
6	National Sanitation Foundation Water Quality Index (NSFWQI) (Noori et al., 2019; Shokuhi et al., 2012; Poonam et al., 2013)	9 Parameters: dissolved oxygen (DO), fecal coliform, pH, biochemical oxygen demand (BOD), temperature, total phosphate, nitrate, turbidity, total solids. Water Quality Levels: Excellent (90–100), Good (70–90), Medium (50–70), bad (25–50), very bad (0–25).	USA. Extended Version of Horton, Dinius Water Quality Index (DWQI).	River, Streams, Canals, Lakes, Wetland.
7	West Java Index (WJI) (Sutadian et al., 2018)	13 parameters: Temperature, Total solids, DO, COD, CL-, Fecal Coliform, Total Phosphate, Nitrates, Mn, Cu, Hg, Pb, Detergent. Water Quality Levels: Excellent (90–100), Good (90–75), Fair (75–50), Marginal (50–25), Poor (25–5).	Indonesia. Adopted from Storet Index and WPI. Modified version of NSF.	River. Other contaminated sources.
8	Almeida Index (Qi et al., 2022)	8 Parameters: pH, Turbidity, COD, Fecal Coliforms, Total Coliforms, Total Phosphate, Total Nitrates, Detergent. Technique Used: Delphi. Water Quality Levels: Excellent (91–100), good (81–90), medium (71–80), poor (<25), poor (<70).	Argentina.	River. Surface water source.
9	Malaysian Index (Koki et al. 2019)	6 parameters: pH, DO, BOD, COD, Suspended Solids, NH3–N. Water Quality Levels: Parameter based individual rating scale used.	Malaysia.	River, Ponds Most of the other surface water sources.
10	British Colombia Index (Lumb et al., 2011; Poonam et al., 2013)	Parameters not specified. Water Quality Levels: excellent (0–3), good (4–17), fair (18–43), borderline (44–59), poor (60–100).	Canada.	Most of the Surface water sources.
11	Smith Index (Smith 1990; Poonam et al., 2013)	Minimum 7 Parameters: DO, BOD, Turbidity, Temperature, Suspended Solids, NH3–N, Fecal Coliform. Parameter Selection: Delphi technique. Water Quality Levels: No classes specified.	New Zealand.	Rivers and streams.
12	Horton index (Abbasi and Abbasi 2012)	8 Parameters: pH, DO, Specific Con., Alkalinity, Cl-, NH3–N, F. Coliforms. Other parameters added on expert opinion. Water Quality Levels: Very good (91–100) Good (71–90), Poor	USA.	Most of the other surface water sources.

(continued on next page)

Table 6 (*continued*)

No	WQI Model Name	Parameters	Origin	Usage
		(51–70), Bad (31–50), Very bad (0–30).		
13	Dojildo Index (Barbulescu et al., 2021)	19 parameters: pH, DO, BOD, COD, Cl-, NH3–N, Suspended Solids, Total Phosphate, Total Sulfate, Total Nitrates, Total Hardness, Total Nitrogen, Cd, Mn, Zn, Cu, Hg, Pb, Phenols. Used common monitoring parameters. Water Quality Levels: Very clean (75–100), clean (50–75), polluted (25–50), very polluted (0–25).	Poland.	River Water.
14	House index (House 1989).	9 Parameters: pH, DO, BOD, Cl-, NH3–N, Total Coliforms, Temperature, Suspended Solids, Total Nitrates. Parameter selection: Expert opinion and use. Water Quality Levels: high quality (71–100), reasonable quality (51–70), moderate quality (31–50), polluted (10–30).	UK. Refined version of SRDD index	Most of the water sources.
15	Environmental Quality Index (Katyal 2011)	9 Parameters: Suspended Solids, Color, Cl-, Fecal Coliforms, Total Phosphate, cd, Zn, Cu, Hg. Adopted Delphi method. Water Quality Levels: excellent (90–100), very good (80–89), good (70–79), fair (55–69), poor (<55).	Northern America.	Most of the other sources.
16	SRDD Index (Uddin et al., 2021)	10 Parameters: Temperature, SS, pH, DO, BOD, Specific Con., NH3–N, Fecal Coliforms, Total Phosphate, Total Nitrogen. Technique Used: Delphi. Water Quality Levels: clean (90–100), good (80–89), good with treatment (70–79), tolerable (40–69), polluted (30–39), several polluted (20–29), piggery waste (0–19).	Scotland.	Surface water sources.
17	Oregon Index (Cude 2001; Poonam et al. 2013)	10 Parameters: Temperature, SS, pH, DO, BOD, NH3–N, F. Coliforms, T. Phosphate, T. Nitrates, T. Nitrogen. Technique Used: Delphi. Water Quality Levels: Excellent (90–100), good (85–89), fair (80–84), poor (60–79), very poor (<60).	Northern America. Refined version of NSF index.	Wetland, River. Most of the other sources.
18	Dinius Index (Abbasi and Abbasi 2012; Uddin et al., 2021)	11 Parameters: Temperature, Color, pH, DO, BOD, Specific Con., Alkalinity, Cl-, Fecal Coliforms, Total Coliforms, Total Hardness. Technique Used: Delphi. Water Quality Levels: Purification not required (90–100), minor purification required (80–90), treatment required (50–80), doutful (40–50).	USA. Modified version of NSF.	River.
19	Ross Index (Uddin et al., 2021)	4 General Parameters: Suspended Solids, DO, BOD, NH3–N. Technique Used: Delphi. Classification of result not specified.	USA. Modified version of NSF.	River.
20	Bascaron Index (Uddin et al., 2021)	26 Parameters Suggested: Temperature, Color, Turbidity, pH, DO, BOD, Specific Con., Cl-, NH3–N, Total Coliforms, Total Sulfate, T. Nitrates, T. Hardness, Detergent, etc. Used Delphi Technique. Water Quality Levels: Excellent (90–100), Good (70–90), Medium (50–70), Bad (25–50), Very bad (0–25)	Spain. Modified version of SRDD.	River, sea. Other surface water sources.
21	Dalmatian Index (Abbasi and Abbasi 2012; Uddin et al., 2021)	8 Parameters Suggested: Temperature, DO, BOD, T. Coliforms, T. Phosphate, T.	Southern Croatia. Modified version of SRDD.	Sea, Marine, Coastal.

(continued on next page)

Table 6 (*continued*)

No	WQI Model Name	Parameters	Origin	Usage
		Nitrogen. Parameter selection: Expert opinion and use. Used Delphi Technique. Categories not specified.		
22	Liou Index (Uddin et al., 2021)	13 Parameters Used: Temperature, Turbidity, SS, pH, DO, BOD, Specific Con., NH3–N, F. Coliforms, Cd, Zn, Cu, Pb. Parameter selection based on environmental and health significance. Technique Used: Delphi. Categories not specified.	Taiwan.	River.
23	Said Index (Abbasi and Abbasi 2012; Uddin et al., 2021)	5 Parameters: Turbidity, DO, Specific Con., F. Coliforms, T. Phosphate. Parameter selection based on environmental significance. Used Delphi Technique. Water Quality Levels: Three classification from 0 to 3, highest purity (3), marginal quality (<2).	USA.	Sea, Coastal.
24	Hanh Index (Uddin et al., 2021)	8 Parameters: Turbidity,SS, DO, BOD, COD, Cl-, T. Coliforms. Parameter selection based on monitoring data availability. Water Quality Levels: Excellent (91–100), good (76–90), fair (51–75), marginal (26–50), poor (<25).	Vietnam.	River.

et al., 2019; Hossain and Patra 2020; Lobato et al., 2015) and *Rating Curve Functions* (Fulazzaky et al., 2010; Othman and Alaa Eldin 2012). Most of the WQI models use these procedures (Lumb et al. 2000; Abbasi and Abbasi 2012; Sutadian et al. 2018), however, few models skip this conversion process, e.g., the CCME model and the Dojildo model (Glozier et al., 2004; Barbulescu et al., 2021).

(Step 3) Selection of weights for the parameters:

Each parameter of the WQI model is assigned a weight relative to its' importance and in according to the water quality measurement guidelines (Sarkar and Abbasi 2006). Most of the WQI models adopted unequal weighting techniques,meaning, a parameter weight is assigned based on its' relative importance in measuring the WQI. However, few other WQI models use an equal weighting approach (Poonam et al., 2013; Abbasi and Abbasi 2012) with some do not use the weighting technique at all (Lumb et al., 2006; Smith 1990; Barbulescu et al., 2021).

Two methods are used to obtain the weight values, namely, The Analytic Hierarchy Process (AHP) method (Sutadian et al. 2018) and The House Index Method (House 1989). It is advised that the weights for the same WQI model should be adjusted depending on the model application to improve the measurement accuracy (Poonam et al., 2013; Gorde and Jadhav, 2013a). Therefore, parameter weights should differ for the same model applied for river and marine waterbodies, respectively (Ewaid and Abed 2017). A suggestive guideline for parameter weight selection can be found in (Akter et al., 2016). The selection of appropriate parameter weights has a deep influence in measuring the final WQIvalue (Step 4), therefore, contributes highly to the models' robustness by reducing the uncertainty in the WQI model, and improving the model integrity (Pham et al., 2022). On the contrary, inappropriate weightings affect the model performance adversely (Dash and Kalamdhad 2021).

(Step 4) Use of aggregation function to calculate WQI:

The aggregation function is applied to the weighted sub-indices to produce a single water quality index score (Sutadian et al., 2018). The index score is evaluated against a rating scale to categories/classify the water quality. The rating scale is specific to a WQI model and varies significantly from model-to-model (Poonam et al., 2013). There are several aggregation functions that are adopted by the WQI models, namely, *Additive Functions, Multiplicative Functions, Combined Aggregating Functions, Square Root of the Harmonic Mean Function, Minimum Operator Function*, and *Unique Linear/non-linear Aggregation Functions* (Abbasi and Abbasi 2012; Poonam et al., 2013; Gorde and Jadhav 2013a).

Adoption of these four steps may vary depending on the WQI Models. Therefore, it is advisable to consult the specifications of a WQI Model for the selection of parameters, and adoption of associated weighting process, the sub-indexing method and the aggregation function (Debels et al., 2005; Abbasi and Abbasi 2012).

6.1.1. Handling WQI model uncertainty

All WQI indices are derived based on a mathematical aggregation function and therefore, uncertainty in the model performance is unavoidable (Lowe et al., 2017). Researchers identified that this uncertainty in due to all the four steps followed in measuring the WQI indices, and the model eclipsing problem.

The *Eclipsing Problem* arises while the WQI model output do not reflect the true nature of the water quality parameters (Uddin et al., 2021). This problem, according to the researchers, is caused by inappropriate selection of sub-indexing rules or parameter weightings, which distort the true relative influences of the parameters, or using inappropriate aggregation functions. Therefore, following actions should be taken to minimize the WQI model uncertainty and the eclipse problem, (a) select the justifiable number of parameters, (b) ensure the quality of parameter values (Ma et al. 2020), (c) collect comprehensive set of data (Ongley and Booty 1999) that is required for the model performance, (d) carefully select the sub-indexing rules and weighting factors that do not conceal the parameter's importance/influence (Swamee and Tyagi 2000), and finally, (e) select a minimum operator aggregation function (Abbasi and Abbasi 2012).

6.2. Pollution index (PI) models

PI models, unlike the WQI models, measure the water quality in terms of the degree or level of pollution of the surface water bodies (Karami et al., 2012; Prathumratana et al., 2008; Sarkar et al., 2019). In general, pollution indices are generated by evaluating the Heavy Metal (HM) concentration in the water bodies or in the sediments (Islam et al., 2018). Among the HMs, the Lead (*Pb*), Iron (*Fe*), Copper (*Cu*), Zinc (*Zn*), Manganese (*Mn*), Nickel (*Ni*), Cadmium (*Cd*), Arsenic (*As*), Cobalt (*Co*), Mercury (*Hg*) and Molybdenum (*Mo*) are the most measured parameters for surface water pollution indexing (Parsad and Bose 2001; Kumar et al., 2019). HMs are often characterized by their long persistence, bioaccumulation and biomagnification in the aquatic compartments. Therefore, they have particular significance in causing toxic effects at points far from the source of pollution (Tripathee et al., 2016; Tian et al. 2015; Wepener 2012). Being non-degradable, they constantly bio-accumulate in freshwater bodies (Chowdhury, Jahan, Islam, Moniruzzaman, Alam, Zaman, Karim and Gan 2012a) and eventually being adsorbed onto the sediments, causing benthic organisms to devour at varying degree, and subsequently to the food chain (Kawser Ahmed et al., 2016; Adimalla and Qian 2019).

Therefore, PI Models and associated standard guidelines are developed primarily for assessing the ecological consequences of the surface water pollution, and sediment pollution due to the HMs (Banu et al. 2013). These PI models can be classified along two broad categories, the *Heavy Metal Pollution indices and Sediment Pollution indices*. To measure the heavy metal pollution, models like Heavy Metal Pollution index (*HPI*), Heavy Metal Evaluation index (*HEI*), Degree of Contamination (*Cd*) and Toxicity Load, are used. On the other hand, for the sediment pollution measurement, the models like, Enrichment Factor (*EF*), the Geoaccumulation Index (I_{geo}) and the Anthropogenic Enrichment Assessment (*IAP*), are used. These models often calculate the anthropogenic fraction of HMs in the water bodies (Tian et al., 2015). In Table 7 an encyclopedic documentation of the PI models and Sediment Index models is presented.

PI models generate a single index value as a pollution indicator, following the identical approach of WQI models (Poonam et al., 2013). This index value is then assessed against the standards and ideal values to classify it within a range of highly pollutant to low pollutant water (Parsad and Bose 2001; Kumar et al., 2019). Analogous to the 4 Step WQI model (as discussed above), the *first step* of this process is to determine the number of parameters to be evaluated based on specific type of pollution to be measured. The *second and third step* is to calculate the sub-indices and relative weighting factor for each HM parameter, respectively, based on their relative importance in measuring the pollution index. *Finally*, apply an aggregation function over the indices and weights to calculate the pollution index value (Abbasi and Abbasi 2012; Swamee and Tyagi 2000). The sub-indices and the weight factor calculation in the second and third steps are optional and depends on the pollution index model under consideration Boyacioglu (2006). For example, the *HPI* model calculates the sub-indices for each pollution parameter and assigns a rating as weight to each of them on their relative significance for calculating the HPI (Ustaoğlu et al., 2021). However, other indexing models, such as *HEI* (Kabir et al. 2020), and (Kumar et al., 2019) use the parameter values directly in the aggregation function, omitting steps two and three.

6.2.1. Handling PI model uncertainty

Results produced by a PI model might not reflect the actual pollution status due to several considerations. For instance, use of absolute values of heavy metal concentrations with equal severity in terms of their biological consequences, would lead to *model eclipsing problem* (Uddin et al., 2021). Therefore, to derive conclusive evaluation of the pollution status when applying a PI model, each HM concentration should be considered according to its' expected toxicity (i.e., sub-indexing) and the overall pollution load that an area is experiencing (through index weighting) (Poonam et al., 2013).

Alongside, use of different pollution index models for the same water body could lead to different pollution status and thus ended up with different conclusions (Sutadian, Muttil, Yilmaz and Perera 2016a). This differentiation is due to the formulation of the specific indices and the use of distinct aggregation functions. For instance, the aggregation function for *HPI* model uses the maximum acceptable value, unit weightage, the standard permissible value and highest desirable value for each HM (Reza and Singh 2010) as an input, whereas the aggregation

Table 7
PI Models for Spatial and Temporal Water quality profiling.

No	PI Model	Parameters	Assessment Criteria	Usage
1	Heavy metal pollution index (HPI) (Parsad and Bose 2001; Kurnaz et al. 2016; Kumar et al., 2019)	10 Parameters: *Fe*, *Cu*, *Zn*, *Cr*, *Mn*, *Co*, *Ni*, *Cd*, *As* and *Hg*. Parameter selection Depends on expert opinion and use.	Five Classes: Excellent (<25), Good (26–50), Poor (51–75), Very Poor (76–100), Unsuitable for drinking (>100).	River, sewerage. industrial waste and effluents, hospital wastes, municipal waste and recreational operations.
2	Heavy metal evaluation index (HEI) (Kumar et al., 2019; Kabir et al., 2020)	Parameters are not fixed. HM parameters are selected based on need. Parameter selection depends on expert opinion and use.	Three Classes: Low (<10), moderate (10–20) and highly polluted (>20)	River. Contaminated water sources.
3	Contamination Index (Cd) (Kumar et al., 2019; Kabir et al., 2020)	Parameters are not fixed. HM parameters are selected based on need. Parameter selection depends on expert opinion and use.	Three Classes: Low (<1), moderate (1–3) and highly pollution (>3)	River. Contaminated water sources.
4	Water Pollution Index (WPI) (Hossain and Patra 2020)	19 water quality parameters: *pH*, *EC*, *TDS*, *Na*+, *K*+, *Mg*2+, *Ca*2+, *F*−, *HCO*3−, *Cl*−, *NO*3−, *SO*2 4, *Zn*2+, *Cd*2+, *P b*2+, *Cu*2+, *Ni*2+, *Co*2+, Total *Fe* (*Fe*2++*Fe*3+).	Four Classes: Excellent quality (WPI< 0.5), good (0.5 > WPI <0.75) and moderately polluted (0.75 > WPI <1), highly polluted (WPI >1).	River and Ground Water
5	Overall Index of Pollution (OIP) (Shukla et al., 2017; Sargaonkar and Deshpande 2003)	Parameter selection Depends on expert opinion and use.	Five Classes: Excellent - Class C1 (0–1), Acceptable - Class C2 (1–2), Slightly polluted - Class C3 (2–4), Polluted - Class C4 (4–8), Heavily polluted - Class C5 (8–16).	River.
6	Aquatic Toxicity Index (ATI) (Wepener 2012)	14 parameters: *pH*, *DO*, *Mn*, *Ni*, *F*, *Cr*, *P b*, *NH*+ 4, *Cu*, *Zn*, Orthophosphates, *K*, Turbidity, Total Dissolved Salts.	Three Classes: Suitable for all fish species (60–100), Suitable only for tolerant fish species (51–59), Totally unsuitable for normal	River and other water sources for fish.

(continued on next page)

Table 7 (*continued*)

No	PI Model	Parameters	Assessment Criteria	Usage
			fish life (0–50).	
7	Nutrient pollution index (NPI) (Ustaoğlu et al., 2021)	Parameters are not fixed.	Three Classes: No pollution (<1), moderate polluted (1–3), considerable polluted (3–6), very high polluted (>6)	River and Other drinking water source.
8	Enrichment factor (EF) (Karaouzas et al. 2021)	Parameters are not fixed. However, according to some guidelines following HMs are used, *Cu*, *Ni*, *Cd*, *Cr*, *P b*, *As*, *Hg*, *Zn*, *Al*, *Fe*, Organic Carbon, *Li*.	Seven Classes: Unpolluted (<1) Slightly Polluted (1 < EF < 3) Moderately Polluted (3 < EF < 5) from Moderately to heavily Polluted (5 < EF < 10) Strongly Polluted (10 < EF < 25) from Strongly Polluted to Extremely polluted (25 < EF < 50) Extremely Polluted (EF > 50)	Generic to all sources.
9	Geoaccumulation Index (*Igeo*) (Karaouzas et al., 2021)	Parameters are not fixed.	Seven Classes: Unpolluted (<0) Slightly Polluted (0–1) Moderately Polluted (1–2) from Moderately to heavily Polluted (2–3) Strongly Polluted (3–4) from Strongly Polluted to Extremely polluted (4–5) Extremely Polluted (>5)	Generic to all sources.
10	Anthropogenic enrichment assessment (*IAP*) (Karaouzas et al., 2021)	Parameters are not fixed.	Seven Classes: Unpolluted (<1.5) Slightly Polluted (1.5< mCD <2) Moderately Polluted (2< mCD <4) from Moderately to heavily Polluted (4< mCD <8) Strongly Polluted (8< mCD <16) from Strongly Polluted to Extremely polluted (16< mCD <32) Extremely Polluted (mCD >32)	Generic to all sources.

function for the *Cd* model uses the division between monitored value and the maximum acceptable value, and includes an additional subtraction of unity (Bhuiyan et al. 2016). Furthermore, pollution index evaluation criteria vary from model to model with different standards and ideal value ranges (Kabir et al., 2020). Therefore, the *Cd* model appears stricter than *HPI* and *HEI* models, and a preferable choice for the evaluation of a study area (Kumar et al., 2019).

6.3. Statistical methods for model optimization

It is the necessity to apply appropriate statistical methods when analyzing water quality data. These statistical methods provide robust scientific inference to draw a global vision and pattern of changes in water quality in space and in time (Drasovean and Murariu 2021; Drasovean et al., 2018). This time-series evaluation can assist in evidence-based decision making for the water regulatory bodies, provide actionable advice regarding water management and to draw valid conclusions (Drasovean et al., 953 2019; Nguyen and Huynh 2022). In the related research, a wide range of statistical methods are applied for time series profiling and prediction of the water quality. This includes, for example, Cluster Analysis (CA), Principal Component Analysis (PCA), Multivariate Statistical Analysis, Entropy Weighted methods (Nguyen and Huynh 2022), Pearson and Spearman Correlation Coefficients (Drasovean and Murariu 2021), Generalized Least Squares, Linear Mixed and Generalized Linear Mixed-effect model and Bayesian Techniques (Parmar and Bhardwaj 2014). Table 8 provides an elaborated listing of these methods along with the tools and techniques utilized in measuring them for a specific water quality assessment.

However, the selection of appropriate statistical methods, their experimental design and selection of tools are pivotal to achieve accuracy in the data analytical processes (Iticescu et al. 2019; Drasovean and Murariu 2021). For example, CA can be conducted in order to find the associations among the parameters, whereas PCA can assist reducing certain variables to determine the indices which can describe the variation in the water quality data with minimal loss of information (Noori et al. 2010). This process of parameter reduction using PCA is especially useful for those countries where resources for operational water quality modelling are scarce (Ustaoğlu et al., 2021). Alongside, to draw a linear relationship between two parameters of water samples, Pearson Correlation Coefficient can be used, while, for non-linear correlation the Spearman Coefficient is appropriate (Iticescu et al., 2019). Nevertheless, this selection must accommodate the uncertainty, inconsistency and variability of the environmental data, and the temporal and spatial dependency structures (Drasovean et al., 2018; Tyagi et al. 2013). Considering the data variability, in (Parmar and Bhardwaj 2014) Generalized Least Squares, Linear Mixed and Generalized Linear Mixed-effect models, and Bayesian Techniques are used to achieve better accuracy in prediction. Finally, applied models can be validated using different standard methods, that includes, Root Mean Square Error

Table 8
Multivariate statistical analysis methods.

No	Methods	Tools Used	Techniques	Research Purpose
1	Cluster Analysis (Nguyen and Huynh 2022; Ustaoğlu et al., 2021)	IBM SPSS 26. Shapiro–Wilk test. Wilcoxon signed-ranks test.	Mean, lower and upper quartile, mode, median and standard deviation. Boxplot diagrams.	Change in sewage network over the time.
2	Principal component analysis (Noori et al., 2010; Ustaoğlu et al., 2021)	Not Specified.	Five major steps: 1) coding the variables (X1, X2, …, Xp) to have zero means and unit variance; 2) calculate the correlation matrix R; 3) find the eigenvalues λ1, λ2,…, λ*p* and the corresponding eigenvectors *a*1, *a*2,…, *ap*; 4) discard any components with a small proportion of the variation in data sets; and (5) develop the factor loading matrix and perform a Varimax rotation on it.	For reducing complexity of input variables.
3	Canonical correlation analysis (Noori et al., 2010)	Not Specified.	Form two canonical variables (U = X and V═Y), a correlation matrix (p + q) × (p + q) between the variables ((X1, X2,…, Xp and Y1, Y2,…, Yq)), Calculate eigenvalue (1 N2 N … Nr) problem equation from the matrix. Coefficients of the canonical variates are for standardized X and Y variables.	An exploratory tool, used as a data reduction method.
4	Factor Analysis (Boyacioglu 2006; Kumar et al., 2019)	Finding different factors.	Three stages of Factor analysis: For all the variables a correlation matrix is generated. Factors are extracted from the correlation matrix based on the correlation coefficients of the variables. To maximize the relationship between some of the factors and variables, the factors are rotated.	Explain the correlations between the observations in terms of the underlying factors, which are not directly observable.
5	Regression analysis (Parmar and Bhardwaj 2013)	Not Specified.	Calculate the correlation and regression coefficients. Standard deviation of variables. Find the expected value and determine the regression line by variables (dependent and independent)	Modeling and analyzing the variables. Understanding the variation in value of the dependent variable.
6	Entropy Weighted Method (Dash and Kalamdhad, 2021)	Not Specified.	Four steps: Step 1: Formulation of dataset matrix. Step 2: Normalization of the dataset matrix. Step 3: Computation of information entropy and entropy weights. Step 4: Estimation of Result.	Correlation with the observed dataset and their uncertainties of occurrence.

(RMSE), R-Squared, Mean Absolute Error (MAE), Maximum Absolute Error, Mean Absolute Percentage Error, Maximum Absolute Percentage Error, Normalized Bayesian Information Criterion, Ljung–Box Analysis, Predicted value and Confidence limits (Parmar and Bhardwaj 2014; Drasovean et al., 953 2019; 2018; Drasovean and Murariu 2021).

7. Pave to the future research

This section opens a broader discussion on the potential future research directions pertaining to surface water quality measurement and monitoring. In doing so, the reported results, and the suggestions for future research are categorically assessed and documented from the reviewed articles. This categorization identified two plausible research directions, namely, (a) design and development of a tech-savvy surface water quality monitoring, and profiling systems, and (b) amelioration of the WQI and PI models in relation to their uncertainty and eclipsing issues.

7.1. On the Water Quality Monitoring System (WQMS)

Realizing the severity of water contamination, governments throughout the world have issued definite directives for acquiring adequate information about surface water for exhaustive water quality assessment and management (Dong et al. 2015; Uddin et al., 2017b; Samad et al., 2013). However, the current process of measuring surface water quality mostly requires laboratory-based manual sample collection and measurement, where samples are collected from the pre-defined points in the rivers and from the effluent treatment plants. This approach is identified as tardy, time-consuming, expensive, ad-hoc, error-prone, and untraceable (Bo et al., 2022). It hinders timely measurement, assessment, decision-making, and long-term planning for water quality assurance (Geetha and Gouthami 2016). Alongside, this approach requires an ample amount of expert workforce with logistic support, which many of the governments cannot afford and maintain (Gholizadeh et al., 2016).

Therefore, the design and development of a tech-intensive, autonomous Water Quality Monitoring System (*WQMS*) is essential to reflect on the vacuum in current processes and practices. The system should enable autonomous, safe, timely, and comprehensive water quality data collection through a self-operated process with minimum human supervision and intervention (Kamienski et al., 2019). It should also maximize the autonomous Remote Sensing (RS) of geo-tagged sensor data (Balla et al., 2022; Glasgow et al. 2004) for periodic or real-time sensor data logging to the remote cloud server for further processing. The server should integrate the statistical methods, AI-driven big data processing, reasoning, prediction and decision support system (DSS) for automated/semi-automated data post-processing, visualization, and decision-making (Lowe et al., 2022; Chen et al., 2020). Therefore, this system can effectively serve the purpose of every concerned stakeholder, namely, the government policy makers, the domain experts, the researchers, and the management, alike (Lumb et al., 2006). Fig. 8 recapitulates these requirements in terms of system specifications that should define the terrain of functionalities and features required for a smart-integrated WQMS system. An explicit denotation and interpretation of these characteristics are given below which will open the pave for a tech-intensive water quality profiling research and system development.

7.1.1. Geo-Tagged Parameter Measurement

Geo-Tagging refers to the amendment of *geo-spatial/geographical information* with the *remote sensing* data, e.g., videos/images taken by a drone, data communication over the smartphone, or data collected through sensors from a given location, among others. Geo-spatial information often includes the *latitude and longitude coordinates* of the geographic location along with the data associated with it (Koparan et al. 2020). If needed, geo-tagging may include *geocoding*. This means having a text-based description of a location (i.e., street addresses, towns, postal zip codes) along with geo-spatial information for better comprehending the location.

Geo-Tagging of the data related to water quality parameter measurement and its' logging to the server, plays a pivotal role in making a *WQMS* system highly useable (Bo et al., 2022). It can enhance the sustainable water resources management and development process through location-based water quality forecasting (Parmar and Bhardwaj 2014; Ali and Qamar 2013). For example, based on the geo-location the most optimum WQI model, and appropriate set of parameters (their standard values, sub-indices and weights) can be selected. Additionally, tailored monitoring, assessment and supervision can be done based on the need for a geographic location, and a countrywide taxonomy of water quality profiling can be drawn (Balla et al., 2022; Koparan et al., 2020).

7.1.2. Remote sensing, and real-time Supervision and Control

Remote Sensing (RS) is the process of data acquisition about an object or phenomenon without making physical contact with the object or on-site observation (Bo et al., 2022; Kamienski et al., 2019). In current days, the use of sensor technologies and satellite imaging become an

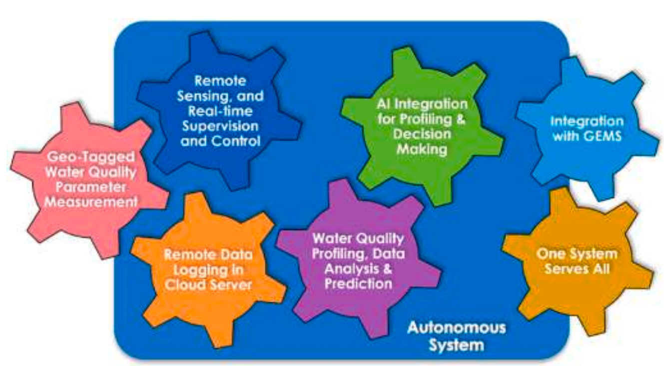


Fig. 8. System Specifications for a smart integrated Water Quality Management System.

integral part of remote sensing (Glasgow et al., 2004; Koparan et al., 2020). The **WQMS** system should have the remote sensing capabilities to operate in real-time. This enables simultaneous deployment of the system in several strategic hot spots where water quality parameters need to be measured automatically in regular intervals (Karim et al. 2021). The deployed system should be equipped with adequate sensors that are configurable remotely for data acquisition (Islam et al., 2020; Kamienski et al., 2019). The sensors should be configured, and polled remotely with graphical visualization and assistance, showing all the critical parameter set by the organization and providing real-time/periodic baseline and trend analysis. Remote management of physical elements and operation of basic units should be part of this vigilance (Balla et al., 2022; Ali and Qamar 2013). Based on the system settings (e.g., frequency of sensor polling and data logging, permissible ranges for measured parameters), the system should automatically monitor and generate alarm/notification (Islam et al., 2020; Geetha and Gouthami 2016).

7.1.3. Remote Data Logging in the cloud server

All data associated with the water quality parameter measurement (e.g., sensor data, laboratory-tested data) must be logged into the cloud data server, either in real-time or in regular intervals (Islam et al., 2020). This server should collect and store the data and send commands and configuration to the field data loggers for controlling the sensors. It must expose required APIs (Application Protocol Interfaces) for information retrieval, processing, manipulation, exchange, and modification for monitoring, remote control and decision-making. This integrated system model that connects the sensors and the cloud system, is an efficient solution to minimize the computational overhead on the sensors and the micro-controllers (Islam et al., 2020; Kamienski et al., 2019). This arrangement increases the power and processing efficiency, extends the lifespan of the sensors and associated components, and lowers the maintenance overhead (Lowe et al., 2022).

7.1.4. Water quality profiling, Statistical Data Analysis and Prediction

Water quality profiling is an effective and economical way to understand the overall health of an ecosystem and the condition of the surface water (Drasovean and Murariu 2021). Profiling allows to monitor of the surface water quality both in spatial and temporal regional variations (Gorde and Jadhav 2013b). To assess the water quality, several *Water Quality Index (WQI)* models, *Pollution Index* models, and numerous *Statistical methods* are deployed for periodic and time-series analysis of the water quality (Schreiber et al., 2022; Parmar and Bhardwaj 2014). An exhaustive list of these models and methods is presented in Section 6.1. The **WQMS** system should possess a high-performance cloud server system that should implement all these models and methods to operate over the logged parameters as per the requirements (Parvin et al., 2022; Balla et al., 2018, 2022).

7.1.5. AI Integration for Profiling and Autonomous Decision Making

Recent research identified that the deployment of artificial neural networks helps in reducing the uncertainty (e.g., eclipse problem) resulting from the final aggregation process of the WQI and PI models (Lowe et al., 2022; Altalak et al., 2022). Therefore, AI tools and techniques should be pursued to reduce model uncertainties and increase the accuracy of the final computed indices.

Alongside, integration of Machine Learning (ML) for AI-driven data-intensive decision-making and controlling is a valuable component for the **WQMS** system (Lowe et al., 2022; Altalak et al., 2022). Due to consistent and continuous logging of water quality data in the cloud server, a complete and comprehensive database is in place for developing diverse ML algorithms. Therefore, the cloud server should provide integration of all the necessary tools, libraries and frameworks (e.g., R, Python Libraries) and allow access to both historical and real-time data for the development, test and run of the ML algorithms (Chen et al., 2020; Wang et al., 2017).

Additionally, there should be an integrated interface for external users (e.g., researchers, academicians, and policymakers) to deploy scripts and run them periodically to get necessary observations and data analytics. The cloud server should offer this interoperability under a given configurations, legislation and collaboration. For instance, exposing authenticated APIs to access data, or exchange data with other authorities under a given model of collaboration, e.g., with the government departments and research organizations managing GIS (Geographic Information Systems) database (Drasovean and Murariu 2021).

7.1.6. Integration to GEMS

Water quality assessment data should be logged into the *Global Environmental Monitoring System (GEMS)* (Gwynne 1982) database as a benevolent contribution towards the better understanding, management and protection of the Earth's environment. Governments all over the world are taking serious initiatives towards this direction. Therefore, the *WQMS* system should expose and implement necessary APIs, authentication mechanism, and protocols that adheres to GEMS guideline for water quality data preparation and periodic logging to the GEMS server (Gwynne 1982).

7.1.7. One System Serves All

There is a wide range of stakeholders that require access to the water quality data and associated analytics for their specific needs. The Government regulatory and monitoring organizations (e.g., the Department of Environment (DoE), Water Development Board, and Public Health Engineering Department) require a comprehensive transcript of water quality assessment for consistent monitoring and supervision of the same to ensure the needs of potable water, irrigation, health, domestic, fisheries and industries. There are other research and educational institutes (e.g., Agricultural Universities, Engineering Universities, the Agricultural Research Institute, and Fisheries Research Institute, among others) that also require access to these data and associated analytic for in-depth research and development in the concerned domains. The *WQMS* system must support configurable system architecture that should meet the needs of these distinct organizations.

7.2. On the quality assessment models

Almost all the research to date, either developed or utilized the WQI models based on a specific usage, sources or pollution pattern of the surface water, as detailed in Section 4, and Column 5 of Table 6. Alongside, from Column 4 of Table 6 it is evident that the model applications are mostly region/site-specific, even though most models are theoretically generic such that they are easily transferable to other sites (Uddin et al. 2017a, 2017b). Therefore, research should be conducted to determine which model suits best for which type of water usage and sources, and how to increase the certainty of model performance in relation to its' applicability to the overall water ecosystem and associated domain in concrete terms (Abbasi and Abbasi 2012).

Furthermore, the application of different WQI and PI models on the same water body in a given geo-location may produce significantly different results, leading to the concern of interpretation, compatibility, and generalizability of the produced quality indices (Abdul Hameed M Jawad et al., 2010). Related studies noted that while most models have broadly similar structures (e.g., the 4-step model detailed in Section 6.1), there is very little uniformity among them at the implementation level, causing inconsistencies in the produced results (Lowe et al., 2017). Therefore, compatibility among the quality indices produced by different models for the same set of parameters and for a given water source should be a core concern of future research.

Several studies highlighted that all four stages of the WQI model (ref to Section 6.1 for detail) can contribute to eclipsing problem and model uncertainty. The eclipsing problem arises when the WQI model output does not reflect the true nature of the water quality parameters and leads to wrong conclusion (Uddin et al., 2021). This situation might occur due to an inappropriate set of parameter selection, or erroneous sub-indexing rules and parameter weightings (Abbasi and Abbasi 2012), or the use of improper aggregation function (Smith 1990). To date, the *Delphi technique* is used to define each stage of the WQI model (Sutadian, Muttil, Yilmaz and Perera 2016b). This technique relies heavily on the survey-based expert panel opinion for parameter selection, development of sub-indexing rules and weighting for the parameters. This process is subject to human biases that might suppress the true relative influences of parameters in calculating the WQI index. Therefore, further research on this track must define a statistically validated evidence-based approach for each of these stages so that the model uncertainty can be minimized.

Finally, almost no WQI model consider using the toxicological components (e.g., heavy metals and nutrients) as part of their aggregation function for measuring the quality indices, as can be verified from Column 3 of Table 6. Therefore, the PI models are being evolved (ref to Section 6.2) to measure the water quality in terms of the degree/level of pollution of the surface water (Karami et al., 2012; Hossain and Patra 2020). However, these models need fine-tuning and verification, like the WQI models to ensure their consistency and compatibility.

8. Validation of the study

Carrying out a literature review is mostly a manual task, and subject to interpretation (Kitchenham et al., 2010). Therefore, researcher bias is the most likely threat to the validity of the reported results (Robinson et al., 2021). To minimize this concern, the biblical process for conducting a SLR is consulted and assumed in detail before commencing this study. In section 3, every step taken for conducting this review is documented with justification. For instance, the research questions are defined based on the review objective, whereas the article inclusion criteria and search keywords are defined based on the research questions. Adhering to the inclusion criteria, articles were collected in a three-step process: automated keyword search in the digital libraries, manual selection of the shortlisted articles, and finally, checking the references for the manually selected ones. This process ensured that the selected articles were both representative, complete and free form reviewer bias (Kitchenham and Charters, 2007; Keele et al., 2007).

Furthermore, the review of the selected articles is subjective and susceptible to researcher bias. This might restrain from reporting the true nature of the research results (Kitchenham et al., 2010; Kitchenham 2004). To mitigate this issue, the domain experts cross-checked the obtained data against the reviewed papers and the research questions to guarantee proper interpretation and presentation (Kitchenham et al., 2010).

9. Discussion and conclusion

Being the ubiquitous source for the majority of water needs the surface water becomes susceptible to significant contamination and pollution. Rapid urbanization and industrialization, inadequate sanitation, overuse and inconsistent monitoring, exacerbate the situation. As a result, the topic of surface water quality testing, monitoring, and management has received major academic interest in recent decades, resulting in an abundance of research. This study therefore, summarized and analyzed the existing research on the concerned domain using the bibliographic SLR approach. This review strived to obtain a comprehensive understanding of the intellectual structure of the water quality assessment research. In summary, this study offers several key contributions by (a) identifying and discussing the landscape of surface water sources, usage and pollution pattern, and their interdependency, (b) derive a detail taxonomy of the water quality parameters concerning their physio-chemical properties and impact on the water sources and usages, (c) revealing comprehensive knowledge clusters on the Water Quality Index (WQI) models, Pollution Index (PI) models and the Statistical methods used for water quality measurement and monitoring, and finally, (d) suggesting the future research directions. Below, the main findings of the review on the surface water quality research is outlined.

A detailed examination of the fresh surface water landscape reveals 13 distinct water sources (e.g., rivers, wetlands, ponds, lakes and so on) that are mostly utilized by five sectors (e.g., agricultural, industrial, domestic, etc.). Practically all of these sectors are the primary source of surface water contamination as industrial effluents, agricultural runoffs, pesticides and fertilizers, and domestic sewage often get deposited in the nearby water sources.

Surface water quality and contamination severity are defined by the assessment of 69 key water quality parameters. However, the selection of these parameters is frequently influenced by a number of critical factors, including the natural properties of the parameters, the purpose for which the water is to be used, the extent to which quality is to be ensured, and the environmental significance of a water quality parameter. As a result, this study carried out a detailed classification of the parameters along these three axes.

Furthermore, this study developed a comprehensive documentation of the water quality assessment models and statistical approaches in relation to parameters, water sources, usage patterns, and model performance. The majority of WQI and PI models have four step evaluation process, e.g., selecting the water quality parameters, determining parameter sub-indices, and assigning weights to the parameters, and finally, applying an aggregation function to compute the overall water quality or pollution index. Although most of the models are generic in terms of portability to other regions or sites, model applications are quite region-specific. The two main issues that affect the accuracy of the model output are the *eclipsing problem and model uncertainty*. All four stages of the WQI/PI models contribute to these issues. For example, the classical *Delphi Technique* that is used for the parameter selection and weightings, often introduces uncertainty and eclipsing effects into the models. Furthermore, as the number of operators in the aggregation function increases, so does the model's uncertainty. Therefore, future research should investigate the role of statistical methods such as principal component analysis and cluster analysis to select parameters and determine their weights. Incorporation of international guideline values (e.g., WHO, EU WFD or similar) may also help to improve the process. The use of fuzzy interface systems and AI-based models can also help in reducing the uncertainty of the aggregate function.

This study also highlights the limitations and practical usability issues of the current manual water quality measurement approaches and argues that the design and development of a technologically advanced, autonomous Water Quality Monitoring System (WQMS) can overcome these limitations. Correspondingly, this study proposes a set of seven system requirements for the development of the same, namely, Geo-Tagged Parameter Measurement; Remote Sensing, and Real-time Supervision and Control; Remote Data Logging in the Cloud Server, Water Quality Profiling, Statistical Data Analysis and Prediction; AI Integration for Profiling and Autonomous Decision Making; Integration to GEMS and One System Serves All. This system should enable safe, timely and comprehensive water quality data collection through self-operated process with minimum human monitoring and intervention. The system should effectively satisfy the needs of many stakeholders including Government policy makers, domain experts and researchers and the management.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

Acknowledgement

This research is partially funed by the RIoT Research Center, Independent University, Bangladesh.

Appendix

Table 9
Reference to the list of primary articles reviewed in this study.

Article Type	Total Count	Reference
Journal	123	Nguyen and Huynh (2022) Lobato et al. (2015) Sánchez et al. (2007) Chowdhury et al. (2012a) Chowdhury et al. (2012b) Syeed et al. (2020) Mama et al. (2021) Carvalho et al. (2011) Debels et al. (2005) Ortega et al. (2016) Pham et al. (2022) Uddin et al. (2021) Drasovean and Murariu (2021) Akter et al. (2016) Lumb et al. (2011) Parsad and Bose (2001) Kurnaz et al. (2016) Kumar et al. (2019) Reza and Singh (2010) Karami et al. (2012) Parmar and Bhardwaj (2013) Balla et al. (2022) Schreiber et al. (2022) Gopaul et al. (2009) Parmar and Bhardwaj (2014) Bartram et al. (2001) Bo et al. (2022) Prathumratana et al. (2008) Islam et al. (2018) Hasan et al. (2019) Lowe et al. (2022) Chen et al. (2020) Altalak et al. (2022) Khan et al. (2021) Ustaoğlu et al. (2021) Tripathee et al. (2016) Chigor et al. (2012) Organization (2022) Griffiths et al. (2012) Lumb et al. (2006) Low et al. (2016) Whitehead et al. (2009) Zhao et al. (2013) Fallah and Zamani-Ahmadmahmoodi (2017) Acharya et al. (2020) Karim et al. (2021) Gholizadeh et al. (2016) Amiri et al. (2021) Shamsuzzaman et al. (2017) Breen et al. (2018) D'Agostino et al. (2020) Rahman et al. (2021) Roje-Bonacci and Bonacci (2013) de Souza et al. (2020) Gerecke et al. (2002) Boyacioglu (2010) Gorde and Jadhav (2013a) Omer (2019) Arora (2017) Lin et al. (2018) Beutler et al. (2014) Chormey et al. (2018) Campanella et al. (2016) Das et al. (2007) Lasheen et al. (1990) Holcomb and Stewart (2020) Champa and Kabir (2018) Barrell et al. (2000) Murariu et al. (2019) Gorde and Jadhav (2013b) Water and Organization (2009) Järup (2003) Chapra et al. (2021) Syafrudin et al. (2021) Jóźwiakowska et al. (2020) Drasovean et al., 953 2019 Noori et al. (2019) Sharma and Kansal (2011) Ferreira et al. (2011) Said et al. (2004) Hsu and Sandford (2007) House (1989) Hernando et al. (2006) Barbulescu et al. (2021) Fulazzaky et al. (2010) Othman and Alaa Eldin (2012) Sarkar and Abbasi (2006) Smith (1990) Abdul Hameed M Jawad et al. (2010) Sutadian et al. (2018) Katyal (2011) Ewaid and Abed (2017) Dash and Kalamdhad (2021) Uddin et al. (2017a) Banda and Kumarasamy (2020) Shokuhi et al. (2012) Qi et al. (2022) Koki et al. (2019) Cude (2001) Lowe et al. (2017) Ma et al. (2020) Ongley and Booty (1999) Swamee and Tyagi (2000) Banu et al. (2013) Tian et al. (2015) Boyacioglu (2006) Kabir et al. (2020) Sutadian et al. (2016a) Tyagi et al. (2013) Iticescu et al. (2019) Noori et al. (2010) Dong et al. (2015) Samad et al. (2013) Geetha and Gouthami (2016) Kamienski et al. (2019) Hossain and Patra (2020) Shukla et al. (2017) Sargaonkar and Deshpande (2003) Karaouzas et al. (2021) Wepener (2012) Koparan et al. (2020) Wang et al. (2017) Sutadian et al. (2016b)
Conferences	4	Islam et al. (2020); Ali and Qamar (2013); Hussen et al. (2018); Drasovean et al. (2018)

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