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REVIEW ARTICLE

Water quality assessment a review in the era of smart technologies: Methods, indices, statistical and geospatial applications

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Abstract

Water quality assessment is crucial for ensuring sustainable water resources management in the face of increasing pollution and climate change. This review examines how methods for evaluating water quality have changed over time, moving from traditional field-based methods to cutting-edge technology like artificial intelligence, remote sensing, and IoT (internet of things)- enabled devices. The evaluation of important physicochemical, bacteriological, and heavy metal factors that affect the safety and usability of water is emphasized. Both surface and groundwater quality are examined in relation to the use of tools like the water quality index (WQI), geographic information systems (GIS), multivariate statistical analysis (MSA), and regression-based machine learning models, such as artificial neural networks (ANN) and Hammerstein-Wiener (HW) models. Strong connections between geospatial analysis, water quality, pollution risk assessment, and statistical analysis are revealed by bibliometric analysis, which also identifies research hotspots and interdisciplinary trends in water quality studies. Through the integration of contemporary data analytics and geographical tools, this review advances the creation of sustainable and comprehensive water resource management.

Keywords: : heavy metals; physical and chemical parameters; remote sensing and GIS; water quality index; water quality monitoring

Introduction

Water quality assessment is an important step toward ensuring the long-term viability and safety of water resources for human use, agriculture, and industry. Among several pollutants, water environmental pollution becomes especially important for sustainable management as a major hazard to human life, health, also the most notable concern (1). Poor water quality poses serious threats to human health, ecosystems, and economic activities, making its evaluation essential for sustainable development. Global changes, including climate variations and human activities such as agricultural runoff, wastewater discharge, landfill leachate, and excessive fertilizer application, have significantly contributed to water quality degradation. Surface water quality is deteriorating due to both natural and anthropogenic factors, including soil erosion, landslides, GLOF (glacial lake outburst flood) events, sediment movement, urban development, industrial, mining, and agricultural operations (2). Groundwater is an important water source for the agricultural purposes, industrial sectors and majorly used as potable water in India (3-5). Groundwater resources, which supply approximately 43 % of agricultural water, are under severe pressure due to urbanization, industrialization, overconsumption and poor management practices (6).

Water quality monitoring programs, typically conducted through field measurements and laboratory analysis, help in assessing the physical, chemical, and biological characteristics of water (7). One of the widely used assessment tools is the WQI (water quality index) , which integrates multiple water quality parameters to provide a composite rating of water suitability. While WQI is extensively used for drinking water assessment, limited research has been conducted on its application for agricultural water evaluation (8). Physicochemical and bacteriological parameters such as pH, temperature, turbidity, salinity, dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), nitrates (NO_3^-), phosphates (PO_4^{3-}), and faecal coliforms are critical indicators of water quality. Additionally, the presence of heavy metals like arsenic (As), lead (Pb), copper (Cu) and iron (Fe) in water sources poses significant health risks through bioaccumulation in food chains (9).

Advanced analytical approaches such as MSA (multivariate statistical analysis) and GIS (geographic information systems) techniques have been instrumental in assessing spatial and temporal variations in water quality (6). The combination of remote sensing, GIS, and water quality approaches enables a thorough understanding of water quality dynamics, spatial patterns, and trends across time. This integrated strategy helps make educated decisions about water source management, pollution control and conservation measures (10). Surface water detection is evaluated using standard water indices including normalized difference water index (NDWI), modified normalized difference water index (MNDWI), water ratio index (WRI), and normalized difference vegetation index (NDVI) (11). For the sake of sustainable development, IoT- enabled AI (artificial intelligence) for water quality monitoring is highly pertinent (12). These methodologies enhance the ability to identify pollution sources, track trends, and develop effective management strategies. This review aims to provide a comprehensive evaluation of water quality assessment methodologies, water quality models, and their applications. By analyzing various parameters, sources of pollution, and modern assessment techniques, this study seeks to contribute to the development of sustainable water management practices that ensure the safety and reliability of global water resource.

Bibliometric analysis

To provide a quantitative overview of the current state of research, we conducted a bibliometric analysis using VOSviewer software. In 2010 VOSviewer introduced, a software tool for visualizing and exploring bibliometric networks, which uses a clustering algorithm to create maps of scientific publications. They demonstrated its application in bibliometric analysis by visualizing co-citation and co-authorship networks (13). Here focusing on the number of publications, which totals nearly 360, including journal articles, review papers, book chapters, and conference proceedings up until 2024, we extracted bibliographic data from Scopus.

Overlay and density visualizations of term co-occurrence were created using this data, exposing significant trends and advancements in the field. The overlay depiction of keyword co-occurrence is shown in Fig 1. This visualization illustrates the connections between a number of research issues in the context of water quality analysis. Terms like "GIS," "water quality," "statistical analysis" and "spatial distribution" exhibit strong clustering, indicating the significance of these concepts in the literature.

Within the larger study landscape pertaining to environmental studies and water quality, the bibliometric visualization identifies ten clear theme clusters. These clusters show interrelated areas of research concentration and are created by closely linked terms that commonly occur together in scholarly papers.

At the centre of the map lies the water quality & GIS cluster, characterized by keywords such as "water quality", "GIS", "statistical analysis", and "spatial analysis". This cluster represents a core theme where geospatial technologies are extensively applied to monitor, model, and manage water quality parameters. The integration of GIS tools with statistical and multivariate analysis methods enables researchers to assess spatial variations in water quality across different regions, facilitating better decision-making in water resource management. The hydrochemistry & groundwater cluster, which includes phrases like "hydrochemistry," "groundwater quality," "ion exchange," and "aquifer," appears in the lower left section. This team investigates factors including pH, alkalinity, hardness, and the presence of ions and trace elements in order to characterize groundwater resources chemically. In order to comprehend the mechanisms determining groundwater composition and to evaluate its suitability for a variety of applications, including drinking and irrigation, studies in this cluster frequently employ methods like factor analysis and hydrogeochemical modeling. With phrases like "health risk assessment," "water pollutants, chemical," "heavy metals," and "drinking water," the human risk & pollution cluster is clearly visible on the right side of the map. Assessing the effects of chemical pollutants on human health, including Pb, As, cadmium, and nitrates, is the focus of this theme area. Health risk models are being used more and more in recent studies in this field to estimate exposure hazards and guide public health initiatives, especially in areas with substantial sources of anthropogenic pollution. Finally, the upper portion of the map is occupied by the remote sensing & land use cluster, which includes phrases such as "remote sensing," "land use," "satellite imagery," and

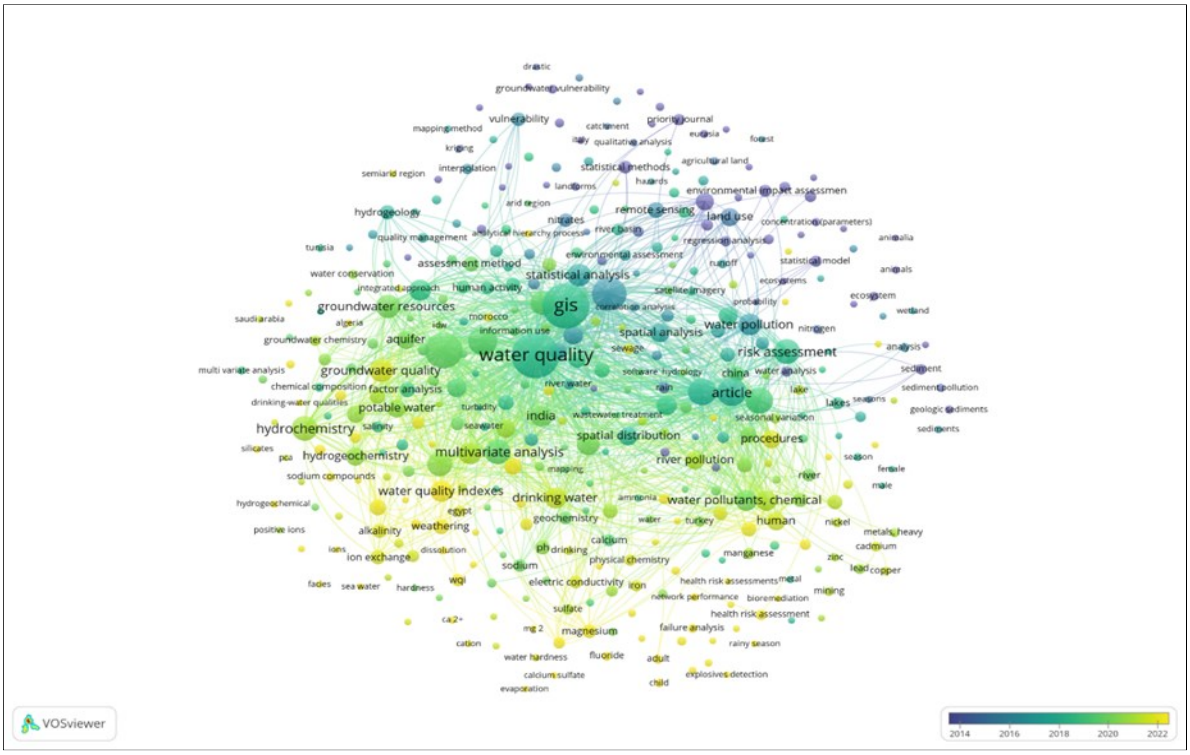

Fig. 1. Visualization of keyword co-occurrence in overlay (VOSviewer software was used to create the figure).

"environmental impact assessment." This cluster focuses on the application of remote sensing technology and land use analysis to investigate environmental changes impacting water systems. Researchers may evaluate the impact of land cover dynamics, agricultural expansion, deforestation, and urbanization on water quality, watershed health, and ecosystem services using satellite data.

Collectively, these clusters offer a thorough understanding of the interdisciplinary character of water-related research, emphasizing how public health concerns, environmental monitoring, water quality analysis, and GIS techniques are all integrated into modern scientific investigation.

Merits and limitations of VOSviewer

VOSviewer specializes at producing intuitive and unambiguous visualizations of bibliometric networks such as co-authorship, co-citation, and keyword co-occurrence. It's capacity to exhibit large-scale data in visually comprehensible clusters makes it extremely useful for identifying patterns in study. Unlike CiteSpace, which can be difficult to use, VOSviewer provides a more accessible and intuitive user interface, particularly for people unfamiliar with bibliometric analysis. In contrast to Web of Science and Scopus, which necessitate institutional access or a subscription, VOSviewer is freely accessible to all researchers, offering broader usability.

While VOSviewer succeeds at network visualization, it lacks advanced bibliometric indicators such as the h-index and impact factor, which are available through programs such as Web of Science and Google Scholar Metrics. These metrics are critical for assessing the influence of writers and publications. While VOSviewer is appropriate for Scopus data, it does not interface as well with other databases like Web of Science or Google Scholar Metrics. These tools provide more extensive citation data and performance metrics from many sources.

Sources of water pollution

Water pollution is usually classified as point and non-point sources (14). Point sources of pollution are those with a direct identifiable source, such as a factory pipe, oil spill from a ship, or industrial effluents. Non-point sources of contamination originate from various non-identifiable sources and infiltrate groundwater or surface water through multiple pathways. Rainwater is a natural source of water pollution as it dissolves contaminants from the air and transports particulate debris. For example, Acid rain occurs when acid gasses, such as sulfur and nitrogen oxides, dissolve in raindrops. Dry deposition, or direct deposition of particulate matter by gravity, is a contributing factor to water contamination (15). The sources of water pollution are briefly summarized in Table 1.

Water quality monitoring and assessment technique

Field measurements and laboratory analysis

Field measurements and laboratory analysis are critical in water quality assessment. The key parameters analyzed in water quality assessment include, COD is the amount of oxygen required to oxidize organic and inorganic materials (12, 30, 31). Biochemical oxygen demand is the amount of oxygen required by microorganisms to break down organic materials. pH is the acidity or alkalinity of water. Dissolved oxygen is the amount of oxygen dissolved in water. Turbidity refers to cloudiness in water caused by suspended particles. Electrical conductivity (EC) measures the flow of electricity and indicates dissolved ions. Temperature affects chemical and biological processes. The oxidation-reduction potential (ORP), which assesses water's oxidation status, reveals the water's ability to release or take electrons during chemical reactions and is a significant characteristic in determining water quality, particularly its compatibility for aquatic life and treatment operations. Salinity is the concentration of salt in water. Total nitrogen (TN) and total phosphorus (TP) are the primary indices of eutrophication and nutrient contamination.

Conventional vs modern monitoring methods

Conventional method

A common method, as utilized by the Central Water Commission, consists of manually collecting water samples from the field and evaluating them in a laboratory environment. Certain places gather water samples within the processing and distribution system, examined in state-of-the-art laboratories (32). Traditional water quality monitoring methods, such as manual sampling and laboratory analysis, have been shown to involve a large amount of human work (33). Large-scale monitoring is difficult to carry out using procedures that require significant manual work and time. Samples are collected at discrete locations and times, which may miss dynamic water quality changes, making them prone to human error and giving limited spatial-temporal coverage. Conventional methods often involve collecting and tracking water samples, which are then examined in a laboratory (19). Mistakes may occur during processing samples in the lab, such as contamination of samples, incorrect titration readings, faulty calibration of instruments, mislabelling of sample containers, and delays in processing that may change sample composition (18).

Table 1. Sources of water pollution

S. No.	Category	Natural sources of pollution	References	Anthropogenic sources of pollution	References
1	Sediment pollution	Soil erosion from natural processes like rainfall and riverbank collapse	(16)	Deforestation and agricultural expansion leading to soil erosion	(17)
2	Nutrient pollution	Natural mineral leaching from rocks and soil	(18)	Excessive use of fertilizers in agriculture leading to eutrophication	(19)
3	Organic pollution	Decomposition of organic matter like plant material and animal waste	(20)	Industrial and agricultural waste discharge containing organic pollutants	(21)
4	Heavy metal pollution	Natural weathering of rocks and volcanic activity	(22)	Industrial effluents from factories, mining, and waste disposal	(23)
5	Microbial pollution	Natural microbial activities in soil and water	(24)	Untreated sewage discharge and runoff from livestock farms	(25)
6	Chemical pollution	Natural leaching of elements like arsenic and fluoride	(26)	Industrial effluents containing chemicals like pesticides, detergents, and hydrocarbons	(27)
7	Salinity pollution	Natural salt deposits and seawater intrusion	(28)	Irrigation practices and industrial wastewater discharge	(29)

Modern monitoring methods

Modern approaches combine real-time data collecting, automation, and advanced analytics to improve monitoring efficiency.

Internet of things (IoT) and smart sensors: Internet of things enables real-time monitoring of water from anywhere in the world with portable sensors, digital computer devices, and communication mediums (34). Internet of things-based sensors continuously monitor pH, turbidity, conductivity, and temperature. Data is sent to cloud systems for instant analysis from the study (12) emphasize the importance of IoT in water quality monitoring by enabling wireless, real-time assessments. Data transmission in IoT-based water quality monitoring systems uses Wi-Fi for internet-connected environments, LoRaWAN for long-range, low-power communication in remote areas, and GSM/GPRS modems for data transfer via mobile networks when Wi-Fi is unavailable (34).

Remote sensing and GIS applications: A study done in Malaysia used satellite pictures from Malaysia's Tiungsat-1 to map water quality on Penang Island (20). The study aimed to quantify total suspended solids and create a water quality map (21). Satellites and drones are used to monitor surface water quality indicators such as chlorophyll-a, total suspended solids (TSS), and turbidity. Also used remote sensing data and GIS techniques to assess water quality at Turkey's Omerli Dam (22).

Artificial intelligence (AI) and machine learning: Artificial intelligence based models such as ANN (artificial neural networks) and adaptive neuro-fuzzy inference systems (ANFIS) forecast water quality trends. Artificial intelligence models can examine enormous datasets, identify abnormalities, and anticipate outcomes (12) examine the application of AI models such as ANN and ANFIS to monitor and assess water quality. The HW model, a machine learning-based system identification technique primarily used for regression tasks, has been effectively applied in modeling DO concentration (35). Internet of things-enabled AI systems for water quality monitoring provide many advantages, ensuring the reliability and validity of the data requires careful attention to sensor selection, calibration, and the application of robust data transmission and validation protocols (34).

Automatic water quality monitoring stations (AWQMS): These stations continuously monitor important parameters and send real-time data. Used for river, reservoir, and coastal monitoring programs. Study emphasizes the usefulness of automated systems for improving data gathering and reducing monitoring gaps (24). The principle of establishing alarm criteria involves setting appropriate thresholds that trigger alerts when water quality deteriorates. In the AWQMS, the existing criteria were too rigid, leading to very few alarms despite potential pollution events. To improve effectiveness, the criteria should be sensitive, relevant to local environmental conditions, and flexible to account for changes like weather and seasonal variations. Benchmarking against international systems can also help refine these criteria, making the monitoring system more responsive and reliable (36).

Water quality index and their applications: Water quality index (WQI) is a mathematical tool used to summarize large amounts of water quality data into a single value, making it easier to understand and compare water quality across different locations and time periods WQIs serve several purposes (37):

I. Simplifying complex water quality data into an understandable form (38)

II. Monitoring water quality over time to identify trends (9)

III. This tool helps policymakers and the public (39).

Applications

Water quality index has been widely applied in different contexts to evaluate water resources. For instance, river and surface water monitoring studies have shown that urbanization significantly impacts river water quality, as observed in Nepal's Bagmati river, where the WQI dropped from 71 (good) to 47.6 (poor) at its discharge point (39). In groundwater assessments, WQI has been used to measure the effects of agricultural and industrial activities, with findings from Bangladesh indicating that most groundwater sources near mining regions were acceptable for drinking, though some showed contamination (40). Similarly, in urban and industrial pollution assessments, WQI was applied in Canada's Mackenzie river basin to analyze pollution from suspended sediments and metals (41). Moreover, climate change and hydrological impact studies have incorporated adjusted WQI models to account for the influence of changing climatic conditions on water bodies (37).

Physicochemical and bacteriological parameters of water quality

Standard methods were adapted for the analysis of various water quality parameters APHA-AWWA-WPCF (1989) (42). In order to evaluate the water bodies' contamination state, the following water quality measures were examined (43) the pH, specific conductance, temperature, total dissolved solids (TDS), and total solids (TS) are the first five factors. Additional influencing factors include total alkalinity, DO, COD, BOD, total hardness, and nutrient concentrations is discussed in Table 2.

pH

pH is an important factor regulating the solubility of minerals and heavy metals in water. Water's pH indicates its acidity or alkalinity. The acidic and alkaline ranges are 0-6 and 8-14, respectively. pH levels between 6.5 and 8.5 are considered optimal. It is measured using electrometry and pH electrodes. It has a strong correlation with EC, total hardness, sulphates, and total suspended solids (31). The optimal pH range for drinking and surface water is 6.5-8.5 found mildly acidic pH values in the Oban Massif of Nigeria, presumably due to rock weathering and agricultural activity (43).

Conductivity

Conductivity refers to the numerical measure of an aqueous solution's ability to conduct an electric current. This property depends on several factors, including the presence of ions, their mobility, concentrations, valence, total ionic content, and the temperature of the solution (28). According to the standards of the Central Pollution Control Board, the acceptable limit is 750 µS/cm, and the permissible limit is 2250 µS/cm (30).

Temperature

It influences the chemistry of water. Higher temperatures accelerate chemical reactions, allowing minerals from nearby rocks to dissolve more easily, particularly in groundwater (34). Water temperature influences chemical reactions and biological activity in aquatic ecosystems. Seasonal changes in the water temperature of the Karnaphuli river in Bangladesh, ranging from 22 °C to 30 °C (44).

Total dissolved solids (TDS)

Water quality is primarily measured by TDS, water contains both organic and inorganic soluble solids, including cations like

Table 2. Physicochemical and bacteriological parameters of water quality

S. No.	Study area	Physicochemical parameters analyzed	Bacteriological parameters analyzed	Key findings & role in water classification	Key findings & role in geochemical processes	References
1	Oban Massif, Nigeria	pH, EC, Turbidity, TDS, BOD, DO	Total coliform and faecal coliform	Water mostly within permissible limits, except for bacteriological contamination	Ion concentrations suggest geogenic sources with some anthropogenic influences	(43)
2	Karnaphuli river, Bangladesh	pH, EC, BOD, COD, TDS, TSS	Total coliform and faecal coliform	High contamination levels, unsuitable for consumption	Industrial discharge and sewage inflow identified as primary contributors to pollution	(44)
3	Albaha, Saudi Arabia	pH, TDS, NO3, SO4, Fe, Mn	Coliform bacteria	Some dam water exceeded permissible levels for pH and dissolved solids	High NO_3 and SO_4 concentrations linked to agricultural runoff	(45)
4	Vaigai river, India	pH, EC, DO, BOD, COD, total hardness, nitrate, chloride	Total coliform and faecal coliform	High EC and TDS indicate pollution; not suitable for drinking	Elevated BOD and COD suggest organic pollution from urban and industrial sources	(46)
5	Nsukka, Nigeria	pH, DO, BOD, chloride, total hardness, TDS, sulfate, nitrate	Total bacteria count and coliform count	Classified water as unfit for drinking due to bacterial contamination; good physicochemical attributes	Presence of nitrates and sulphates linked to agricultural runoff and natural weathering processes	(47)
6	Samaru, Nigeria	pH, EC, DO, chloride, nitrate, hardness	Total bacteria and coliforms	High bacterial load renders water unsafe	Nitrate and phosphate pollution linked to agricultural activities	(43, 48)
7	Ankober, Ethiopia	pH, EC, DO, alkalinity, hardness, major ions	Total coliform and faecal coliform	Water is mostly safe, with localized contamination concerns	Seasonal variation affects ion concentrations due to weathering and dilution	(49)
8	Kidd’s Beach, South Africa	pH, temperature, EC, salinity, turbidity	Enterococcus and total coliform	High bacterial contamination poses health risks	Anthropogenic influences such as sewage discharge contribute to microbial contamination	(50)

magnesium, calcium, sodium, and potassium (34). The permissible TDS range is 500 mg/L, as specified in the standards, beyond which water may not be considered suitable for drinking without proper treatment (34).

Turbidity

Turbid water appears hazy or cloudy, mainly due to suspended particles that are invisible to the naked eye, including fine organic and inorganic matter, silt, clay, algae, and dissolved coloured organic substances (19). A study conducted in the Ankober district of Ethiopia reported turbidity levels ranging from 0.05 to 8.99 NTU, with higher values observed in areas influenced by agricultural runoff (34).

Total hardness and salinity

Water hardness is determined by measuring dissolved bicarbonates, carbonates, sulphates, and calcium and magnesium chlorides. The optimal limit for total hardness is 200 mg/l, while the highest allowed value is 600 mg/L (51). Salinity affects water classification and agricultural appropriateness. That TDS in the dams of the Albaha area in Saudi Arabia surpassed acceptable levels, indicating increased salinity (45).

Dissolved oxygen (DO)

Dissolved oxygen represents the dissolved gaseous form of oxygen. Fish and other aquatic species rely on it for breathing (52).This shows oxygen's solubility in water. Water absorbs oxygen from the atmosphere and creates it through photosynthesis. It is crucial for aquatic life. It is typically measured using an electrometric meter or Winkler titration (31). Dissolved oxygen is vital for aquatic creatures. Dissolved oxygen levels in surface waters of Oban Massif, Nigeria, ranging from 4.0 to 6.5 mg/L, which were appropriate for fish survival (43).

Biochemical oxygen demand (BOD)

Biochemical oxygen demand quantifies the breakdown of organic matter. The Vaigai river in India has BOD levels ranging from 4.5 to 22.6 mg/L, indicating organic contamination brought on by wastewater discharge. Biochemical oxygen demand can be found in a variety of sources, such as leaves and woody debris, dead plants and animals, animal manure, wastewater treatment plant effluents, feedlots, food processing facilities, pulp and paper mills, failed septic systems, and urban storm water runoff (46).

Chemical oxygen demand

The amount of oxygen needed for the chemical oxidation of organic materials with the aid of a potent chemical oxidant is measured by COD (53). Elevated COD could lead to oxygen depletion brought on by microbial breakdown to a point where it is harmful to aquatic life. It was observed that the COD levels in the Karnaphuli River varied between 25.7 mg/L and 86.7 mg/L, surpassing the WHO guideline value of 10 mg/L, thereby indicating significant industrial pollution (44).

Nutrients

Ammonia and inorganic nitrogen are two forms of nitrogen that can infiltrate lakes and streams. Aquatic systems have a plentiful amount of accessible nitrogen because nitrogen can enter them in a variety of ways (52). Elevated nitrogen levels can lead to eutrophication and algal blooms, particularly when phosphorus is also present, as both nutrients often act synergistically to accelerate the process. Phosphorus, like nitrogen, commonly enters water bodies through agricultural runoff, detergents and sewage effluents. For example, nitrate concentrations ranging from 4.51 to 7.51 mg/L in the Vaigai river, suggesting contamination likely due to agricultural runoff. The presence of phosphorus in such contexts can further exacerbate eutrophication and degrade water quality (54).

Heavy metals in water and their health implications

Heavy metals are major environmental pollutants because of their persistence, toxicity, and bioaccumulation in ecosystems. The most frequent heavy metals found in water sources are As, Pb, Cu, Cr, Mn, Fe, and Ni. These metals come from both natural and manmade sources, including as industrial waste, mining operations and agricultural runoff.

Arsenic (As)

Arsenic is highlighted as a major toxic metalloid commonly found in groundwater worldwide and poses significant health risks. In the study area of Kasur, As levels in groundwater samples exceeded the WHO permissible limit of 0.01 mg/L, with concentrations reaching up to 0.82 mg/L (54). The study analyzed As levels in groundwater from 39 wells and 5 reservoirs across five cities in Yazd Province, Iran. As was not detected in any of the samples, indicating it does not currently pose a health risk in the region's drinking water. This contrasts with findings from other regions where As is a significant contaminant linked to health risks (55). Studies indicate a dose-dependent rise in skin cancer mortality due to As exposure in drinking water (56). In Taiwan, individuals exposed to As levels >0.60 mg/L had significantly higher age-adjusted skin cancer mortality compared to those exposed to <0.30 mg/L.

Lead (Pb)

Lead was identified as the most abundant heavy metal in the groundwater samples collected across five zones in Kasur. The maximum concentration of Pb reached 7.47 mg/L, which exceeds the WHO permissible limit of 0.01 mg/L (54). According to the study (57), Pb contamination is primarily caused by leached old plumbing systems, industrial pollutants, battery waste, and mining activities. Pb accumulates in drinking water when deteriorated pipes emit Pb particles, posing a considerable risk to water users (55).

Copper (Cu)

Copper is an essential micronutrient required for various biological functions at trace levels, but it can become toxic at higher concentrations. In the Hyderabad groundwater study, Cu levels ranged from 0.018 to 0.052 mg/L, well below the WHO safe limit of 2 mg/L. Copper can contaminate water through sources such as industrial wastewater, aging or corroded plumbing, and runoff from agricultural activities (58). Copper contamination is often linked to acid mine drainage and chemical manufacturing processes, which release excessive amounts of Cu into aquatic ecosystems in the study area (54). The health implications of Cu exposure involve both deficiency and excess, and the dose-response relationship for Cu is notably U-shaped. This means that both insufficient and excessive Cu levels can result in adverse health effects (59).

Chromium (Cr)

According to study, the electroplating, textile, leather tanning, and industrial waste sectors are the primary sources of chromium pollution (60). Trivalent (Cr III) and hexavalent (Cr VI) forms of chromium are both extremely toxic and carcinogenic (55). Epidemiological studies show a weak link between low-dose chromium exposure from drinking water and changes in biochemical markers like albumin, total proteins, and triglycerides (61).

Manganese (Mn)

Mining operations, industrial waste discharges, and natural deposits all contribute to manganese contamination (62). Groundwater systems frequently have elevated manganese levels in drinking water, especially in regions with significant natural manganese reserves (58). Manganese exposure, particularly from drinking water, is linked to neurotoxicity, with higher concentrations (0.08-2.30 mg/L) associated with neurological impairments. In children, exposure to levels between 0.241–0.346 mg/L affected memory and dexterity (63).

Iron (Fe)

Natural sources, industrial effluents, and deteriorated pipelines are the main causes of Fe contamination (5). Despite being a necessary nutrient, too much Fe in drinking water can cause discoloration and a metallic taste (55).

Nickel (Ni)

Nickel pollution comes from metal plating, mining, and fossil fuel burning (64). Nickel contamination in urban water sources has been related with industrial discharge and atmospheric deposition (54). Chronic exposure to nickel is associated with a tolerable daily intake (TDI) of 13 µg/kg body weight, based on a Benchmark Dose Lower Confidence Limit (BMDL10) of 1.3 mg/kg. For acute exposure, the Lowest Observed Adverse Effect Level (LOAEL) is 4.3 µg/kg body weight, linked to skin reactions in sensitized individuals (65).

Statistical and geospatial techniques for water quality assessment

Remote sensing provides a spatial and temporal view of surface water quality, allowing for more efficient monitoring and quantification of concerns (30). The study explores a variety of sensors and remote sensing platforms that are commonly used to assess water quality. MODIS, SeaWiFS, MERIS, QuickBird, IKONOS, GeoEye, SPOT, WorldView, and Landsat series are some of the regularly utilized space borne sensors (30). In water quality evaluations, multivariate statistical methods including cluster analysis (CA), principal component analysis (PCA), and hierarchical cluster analysis (HCA) are frequently employed. Principal component analysis was applied to identify the origins of the trace elements in the surface waters of Kizilirmak river (66). Relationships between optical (NDVI, NDWI, and MNDWI) and non-optical (TDS, BOD, hardness, and DO) water quality measures were examined in this work using Pearson correlation and scatter plots (11). Regression modeling was utilized to predict non-optical using the factors that were chosen using PCA. The water quality metrics (EC, TDS, Ca, Mg, and total hardness) of a few chosen tanks were analyzed spatially and temporally using box plots. By converting correlated variables into a collection of uncorrelated components, PCA is used to simplify huge datasets. Principal component analysis was employed to identify the main causes of water contamination, including household wastewater, agricultural runoff, and industrial effluents (67). Prioritizing intervention options is made easier by the major components that were identified from the data, which show the primary pollutants influencing water bodies.

Water quality assessment in the study (11, 68) uses multivariate analysis (PCA, CA) to find connections and descriptive statistics to summarize parameters. Whereas ANOVA (analysis of variance) or t-tests assess changes, regression analysis looks at affecting factors. Geographic information systems methods such as overlay analysis evaluates environmental effects and spatial interpolation (Kriging, IDW) forecasts water quality. Hotspots for pollution are seen by thematic mapping, and hydrological influences are better understood through watershed modeling. These techniques improve precision and facilitate efficient water management. A statistical technique called HCA is used to organize water quality data into hierarchical categories. In order to help design targeted water management plans, showed how HCA may be used to group water samples with comparable pollutant characteristics (67). Principal component analysis helps simplify complex data by identifying key variables that explain most of the variation, aiding in the analysis of groundwater quality patterns. Hierarchical cluster analysis groups similar samples based on their properties, helping identify areas with similar or differing water compositions. Both techniques are valuable for understanding and managing groundwater quality efficiently (69). The study was conducted in the Oued Laou Mediterranean Watershed, Morocco. Sample stations were geographically classified using the Euclidean distance and ward linkage approach to determine similarity or dissimilarity. Hierarchical cluster analysis was used in this study to validate the results of PCA (70).

Challenges and future aspects in water quality management

Challenges in water quality management arise from increasing pollution levels due to domestic, agricultural, and industrial sources, making treatment more difficult. Emerging contaminants, such as heavy metals, microplastics, and pharmaceuticals, further complicate water purification efforts (71). Rising temperatures, shifting precipitation patterns, and extreme weather events driven by climate change exacerbate water quality issues and pose challenges for sustainable water management (72). Uneven enforcement of policies and a lack of international cooperation create significant gaps in regulations, hindering effective water management (73). The absence of proper wastewater treatment and monitoring systems in many regions highlights the inadequacy of infrastructure for effective water management (74). High costs and limited access to advanced water treatment technologies create significant technological and financial constraints, hindering effective water management (75). For a future-oriented perspective on water quality protection, public awareness and participation through education and community involvement are essential (73). A holistic approach to sustainability, known as integrated water resource management (IWRM), integrates land and water management to ensure long-term resource efficiency (71). Water purification and quality control can be greatly enhanced by advanced treatment methods, such as membrane filtration, bioremediation, and nanotechnology (76). Additionally, leveraging big data, remote sensing, and real-time monitoring can enhance decision-making and improve water management efficiency. Raising awareness and actively engaging local communities in conservation efforts remain crucial for sustainable water management (74).

Conclusion

Water quality assessment is an important part of long-term water resource management, especially in light of rising anthropogenic demands and climate change. This overview discusses the many physical, chemical, and biological factors used to assess water quality, as well as commonly used classification systems and indices. It also includes an overview of several water quality models, which are useful tools for modeling and predicting water quality dynamics in various aquatic habitats. Each model has a distinct structure, strengths, and limits, so it is critical to choose an appropriate model based on specific goals, data availability, and catchment features. While traditional monitoring methods are accurate, they are typically time-consuming and costly, underlining the growing need for robust, user-friendly modeling approaches. To improve the precision and application of water quality evaluations, future research should concentrate on incorporating cutting-edge technologies including real-time data collection, machine learning, and remote sensing. For policymakers, academics, and water resource managers seeking to preserve and restore water quality across diverse ecosystems, a hybrid strategy that combines field observations with model simulations can provide thorough insights.

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Authors' contributions

VN conducted an extensive literature review, synthesized key concepts and drafted the manuscript. BN supervised the research, ensured the integrity of the review process and approved the final version of the manuscript. KS assisted in refining the research concepts, provided critical feedback on the manuscript and supported access to essential resources. KA helped with content organization, manuscript editing and improving overall clarity and flow. SS carried out analyses, assisted in synthesizing the findings and improved manuscript quality through thoughtful revisions. All authors read and approved the final manuscript.

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