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REVIEW

Emerging Soft Computing Technologies for Groundwater Quality Monitoring, Prediction and Management: A Comprehensive Review

SANTOSH TUKARAM SANAP[1], SHRIKANT BHAUSAHEB RANDHAVANE[1] and SANDHYA SANTOSH SANAP[2,*]

[1]Department of Civil Engineering, SVKM NMIMS Global University, Dhule-424001, India
[2]Department of Artificial Intelligence & Data Science Engineering, SNJB's Late Sau. K.B. Jain College of Engineering, Chandwad, Nashik-423101, India

*Corresponding author: E-mail: sandhya.aghav070@gmail.com

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Groundwater is a vital resource for domestic, agricultural and industrial activities worldwide. Rapid urbanization, industrialization, intensive agricultural practices and climate change have increased the risks of groundwater pollution and depletion. Conventional monitoring methods based on field sampling and laboratory analysis are often time-consuming, costly and limited in spatial and temporal coverage, restricting timely assessment and effective groundwater management. Recent advances in artificial intelligence (AI), machine learning (ML), geographic information systems (GIS), remote sensing (RS) and the Internet of Things (IoT) offer new opportunities to develop integrated monitoring networks to sustain long-term water security through efficient groundwater quality assessment, pollution prediction, contaminant tracking and sustainable water resource management. Following a PRISMA-based screening and eligibility assessment process, 103 relevant studies were selected and systematically analyzed to evaluate recent advances in AI, ML, GIS, RS and IoT applications for groundwater quality monitoring and management This review provides an updated overview of various recent studies and developments concerning the use of AI, ML, GIS, RS and IoT in groundwater monitoring, pollution mapping, health-risk evaluation and intelligent decision-making. It primarily emphasizes on applications of various machine learning algorithms namely artificial neural network (ANN), random forest (RF), support vector machine (SVM), extreme gradient boosting (XGBoost) and deep learning in prediction of groundwater quality and water quality index (WQI). This review also focuses on aspects of spatial analysis using GIS and RS, vulnerability assessment and detection of pollution hot-spot and on-line groundwater quality monitoring through IoT-based networks. In addition, some main challenges such as data availability, interpretability of models, reliability of sensors, cyber security and technology implementation are discussed critically. Potential future applications such as explainable AI (XAI), Digital Twins, edge computing, federated learning and intelligent decision support system (IDSS) are also presented. The study concludes that inter-disciplinary integration of environmental science, geospatial technologies and artificial intelligence can bring about robust, scalable and intelligent groundwater.

Keywords: Groundwater quality, Artificial intelligence, Geographic information systems, Smart groundwater management.

INTRODUCTION

Groundwater is a vital component of global freshwater resources and a major source of water for domestic supply, irrigation and industrial applications [1]. Nearly half of the global population depends directly or indirectly on groundwater for daily water needs [2-5]. Population growth, urbanization, industrialization, intensive agriculture and climate change have placed increasing pressure on groundwater resources, with deterioration in water quality emerging as a major environmental concern [6-8]. From a chemical perspective, contamination by fluoride, arsenic, nitrate, heavy metals, pesticides, pharmaceuticals and other emerging pollutants poses serious risks to human health and ecosystems [9-12]. Prolonged exposure to contaminated groundwater may cause fluorosis, arsenicosis, kidney diseases, neurological disorders and other adverse health effects [12,13].

Conventional groundwater monitoring relies on field sampling and laboratory-based chemical analysis. Although these methods provide reliable measurements of physico-

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chemical properties and contaminant concentrations, they are labour-intensive, time-consuming, expensive and dependent on discrete sampling. Such approaches may fail to capture seasonal variations, sudden contamination events and changes in hydrochemical composition. Limited spatial coverage and inadequate forecasting capabilities further restrict their effectiveness in groundwater management [14,15]. Systematic assessment of pH, electrical conductivity, total dissolved solids, hardness, major ions, nutrients and potentially toxic elements is essential for identifying contamination sources, understanding geochemical processes and evaluating groundwater suitability.

Recent developments in artificial intelligence (AI), machine learning (ML), geographic information systems (GIS), remote sensing (RS) and the Internet of Things (IoT) offer opportunities to integrate hydrochemical measurements with environmental data for improved groundwater assessment. Machine learning techniques can identify complex nonlinear relationships among physico-chemical parameters, geological characteristics, land-use patterns and contaminant concentrations. Artificial neural networks (ANN), random forest (RF), support vector machines (SVM), extreme gradient boosting (XGBoost) and deep learning models have been applied to groundwater quality prediction, contamination assessment and water quality index (WQI) estimation [16-18]. These methods support the interpretation of chemical datasets, identification of potential pollution sources and prediction of groundwater quality variations.

GIS and remote sensing facilitate spatial assessment by integrating geological, hydrogeological, land-use and environmental information. Their application enables the identification of contamination hotspots, evaluation of land-use impacts and preparation of groundwater quality maps across extensive geographical areas [19]. Geostatistical techniques, particularly inverse distance weighting (IDW) and kriging, are widely used to estimate the spatial distribution of chemical constituents and delineate contamination-prone regions [20]. The integration with hydrochemical data improves the interpretation of spatial variations in groundwater composition.

IoT-based monitoring systems enable continuous, real-time measurement of selected water quality parameters using chemical sensors and automated devices. Wireless communication and cloud-based platforms facilitate rapid data collection, transmission, and analysis. Automated monitoring and early-warning systems can detect abnormal changes in water quality parameters and support timely intervention [21-23]. Similarly, the integration with AI and ML models further enables contamination prediction and informed groundwater management.

Important challenges remain concerning hydrochemical data quality, model interpretability, prediction uncertainty, sensor calibration and reliability, data security and monitoring network scalability [5,8]. Addressing these limitations is necessary to establish reliable and sustainable groundwater monitoring frameworks. Existing research often examines ML, GIS, RS and IoT separately, while fewer reviews integrate these technologies into a unified framework encompassing chemical characterization, contamination prediction, health risk assessment, and decision-making. Applications of explainable artificial intelligence (XAI), digital twins, edge computing and federated learning in groundwater management remain comparatively limited. Integrating these emerging technologies with chemical analysis and geochemical interpretation can strengthen monitoring networks and sustain long-term water security.

Methodology of review

The present study systematically reviews the growing application of artificial intelligence (AI), machine learning (ML), geographic information systems (GIS), remote sensing (RS), and the Internet of Things (IoT) in groundwater quality monitoring, contamination prediction and sustainable groundwater management. A systematic review approach was adopted to identify, critically evaluate and the prepare existing research while minimizing selection bias. The review methodology followed the PRISMA guidelines to maintain transparency, consistency, reproducibility in literature identification, screening, eligibility assessment and study selection [24-26].

The review primarily covers studies published between 2015 and 2026, with selected seminal publications from 2008 to 2014 included to establish the theoretical, methodological, and technological foundations. Literature was retrieved from six scientific databases such as Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink and Google Scholar. The search strategy covered groundwater hydrochemistry, water quality assessment, contamination monitoring, predictive modelling, geospatial analysis and intelligent monitoring systems. The several keywords and search phrases were used for example, Groundwater quality monitoring; Groundwater contamination prediction; Artificial intelligence in water quality; Machine learning groundwater; Deep learning groundwater quality; GIS groundwater contamination; Remote sensing groundwater assessment; IoT water quality monitoring; Smart groundwater management; and Water Quality Index prediction.

Boolean operators (AND and OR) were used to combine search terms, with database-specific syntax adapted to improve retrieval accuracy. The search strategy targeted studies addressing groundwater chemical composition, physico-chemical parameters, contaminant distribution, pollution prediction, and technology-assisted groundwater management [27,28].

Study selection criteria: Following the literature search, the identified studies were screened using predefined inclusion and exclusion criteria to ensure consistency and minimize selection bias throughout the review process [27]. The review included peer-reviewed journal articles and conference papers published in English, primarily between 2015 and 2026, with relevant studies from 2008 to 2014 considered where necessary to establish the theoretical, methodological, and technological foundations. Eligible studies focused on groundwater quality assessment, chemical characterization, contamination prediction, monitoring or management using artificial intelligence (AI), machine learning (ML), geographic information systems (GIS), remote sensing (RS), the Internet of Things (IoT), cloud computing, or related computational approaches. Studies were required to provide adequate methodological details and report relevant model evaluation metrics. Publications addressing surface water quality, lacking suffi-

cient methodological information or not primarily concerned with groundwater quality were excluded, along with duplicate records, abstracts, editorials, non-peer-reviewed publications and reports. These criteria helped maintain the relevance, transparency and consistency of study selection.

Screening and eligibility assessment: A total of 724 records were initially identified through database searches of Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore and Google Scholar. After removing 156 duplicate records, 568 records remained for title and abstract screening. Of these, 352 records were excluded as they were not directly related to groundwater quality monitoring, contamination forecasting, AI technologies, GIS, remote sensing or IoT-based groundwater management systems. The remaining 216 full-text articles were assessed for eligibility. Of these, 113 articles were excluded due to insufficient methodological details, limited relevance to groundwater quality assessment, replicated results, lack of peer review or a focus on surface water rather than groundwater. The remaining 103 articles met the inclusion criteria and were retained for further review and synthesis. These studies were examined to investigate the applications of AI/ML, GIS/RS and IoT techniques in groundwater quality prediction, contamination-related health-risk assessment and intelligent groundwater management. The literature selection process comprised four stages *viz*. (i) identification of records through database searching; (ii) removal of duplicate records; (iii) screening of titles and abstracts; and (iv) full-text eligibility assessment, as illustrated in the PRISMA flow diagram (Fig. 1).

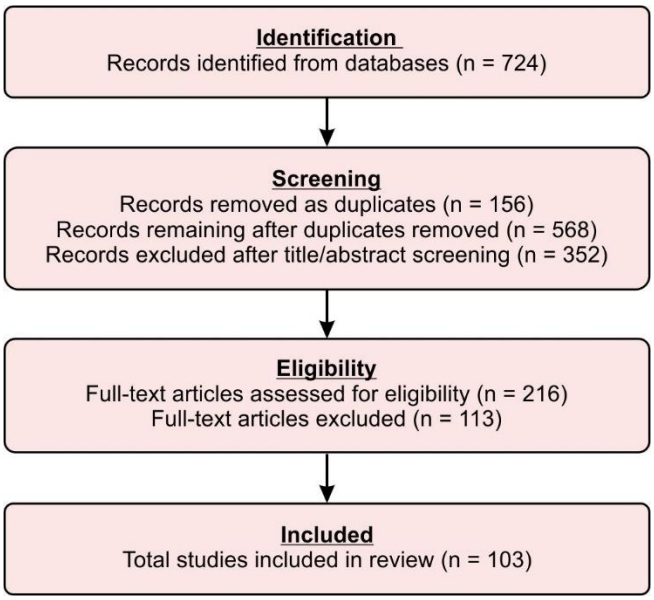


Fig. 1. PRISMA-style flow diagram showing literature identification, screening, eligibility assessment and final study selection process adopted in the present review

Data extraction: Data were extracted from the selected studies using a structured approach to facilitate systematic comparison of the reported research findings. The extracted information included publication year, country or study area, groundwater quality parameters, AI/ML algorithms employed, GIS and remote-sensing techniques, IoT monitoring components, prediction performance metrics, key findings and study limitations. In addition, the comparative assessment considered dataset sources and sizes, prediction targets, model validation strategies and the evaluation metrics reported in individual studies, wherever this information was available. For AI/ML-based studies, the analysis considered the algorithms employed, data partitioning and validation procedures and reported performance measures such as the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE) and classification accuracy, where applicable. GIS and remote-sensing studies were examined in terms of spatial data inputs, groundwater-quality mapping, contamination assessment and validation approaches. IoT based studies were assessed in relation to monitored water quality parameters, sensor systems, data-transmission approaches and reported field-validation evidence. A qualitative comparative analysis was adopted since the reviewed studies differed in their datasets, groundwater characteristics, prediction targets, modelling approaches and performance indicators. Consequently, reported performance values were interpreted in the context of the methods and validation procedures used in each study rather than being treated as directly comparable. Missing information was identified as not reported and findings were interpreted according to the evidence available in the original publications. The extracted information was comparatively analyzed to identify common methodological approaches, variations in reported performance, limitations in validation practices and research gaps in the application of AI/ML, GIS, remote sensing and IoT to groundwater quality monitoring, contamination prediction, health-risk assessment and intelligent groundwater management. The analysis further examined challenges related to hydrochemical dataset availability, model generalizability, sensor reliability and technological integration. These findings provided a basis for identifying research priorities and opportunities to develop more reliable, chemically informed and integrated groundwater monitoring systems [29].

Review scope and novelty: Existing reviews on the groundwater quality have largely focused on contamination sources, hydrogeochemical processes, health-risk assessment or individual monitoring technologies. The present review adopts an integrated, cross-disciplinary approach to examine the applications of artificial intelligence (AI), machine learning (ML), geographic information systems (GIS), remote sensing (RS), and the Internet of Things (IoT) in groundwater quality assessment, contamination prediction and sustainable management. Based on a critical analysis of 103 selected studies, the review explores the complementary roles of these technologies in hydrochemical monitoring, predictive modelling, spatial contamination assessment, health-risk evaluation and decision support. Particular attention is given to the chemical parameters investigated, datasets used, prediction targets, validation procedures and reported performance indicators, where available, to assess methodological differences and limitations. The review examines challenges related to data availability, model interpretability and generalizability, sensor reliability, cybersecurity, technological integration, and practical implementation. Emerging approaches, such as explainable artificial intelligence (XAI), cloud computing,

edge computing, Digital Twins and federated learning, are discussed in terms of their potential applications, limitations and relevance to groundwater management, with due consideration of the limited groundwater-specific evidence for some technologies. The distinctive contribution of this review lies in connecting chemical characterization, monitoring technologies, predictive methods, spatial analysis and health-risk assessment within a unified framework. The identified research gaps and methodological challenges provide a basis for defining future research priorities and developing reliable, transferable and practically applicable groundwater monitoring systems to sustain long-term water security.

Limitations of the review: Despite the efforts made to produce an accurate, thorough and systematic review, certain limitations should be acknowledged. This review included peer-reviewed articles published in English between 2008 and 2026 and indexed in Scopus, ScienceDirect, Web of Science, SpringerLink, IEEE Xplore and Google Scholar. Although the overall review period covered 2008-2026, the primary focus was on studies published between 2015 and 2026, with earlier studies included where necessary to establish methodological, theoretical and technological foundations. Consequently, relevant studies published in languages other than English, unpublished articles, technical reports and other grey literature were excluded. The reviewed studies covered diverse aquifer types, groundwater quality parameters, datasets, modelling techniques and evaluation methods, which may limit direct comparisons across studies.

Research objectives and scope: The continuous enhancement of application of AI, ML, GIS, RS and IoT technologies have led to considerable improvement of groundwater quality monitoring, prediction of contaminations and management of water resource [30]. As such, this review attempts to critically discuss the utilization of emerging technologies in the assessment of groundwater quality and its sustainable management, based on the objectives of the present review as follows: (i) Review of groundwater quality parameters and contaminants indicator; (ii) Assessment of AI and ML methods in the prediction of groundwater quality; (iii) Review of application of GIS and RS in contaminant mapping, (iv) Examination of IoT-based groundwater monitoring system and (v) Identifying the research gaps and future scope in smart water management. The present review covers peer-reviewed studies published between 2008 and 2026, with a primary focus on research published between 2015 and 2026. Relevant earlier studies were included where necessary to provide methodological, theoretical and technological foundations. The reviewed studies address groundwater quality monitoring, contamination assessment, forecasting, predictive modelling and smart groundwater management through the application of AI, ML, GIS, RS and IoT technologies.

Groundwater quality parameters and contamination indicators: Physico-chemical and biological characteristics describe drinking, agricultural and industrial quality of groundwater. Several parameters like pH, electrical conductivity, total dissolved solids, total hardness, major ions, nutrients and trace elements such as fluoride, nitrate, arsenic and heavy metals are generally studied. All these parameter value could possibly relate to the nature of geological or anthropogenic processes which are influencing the groundwater chemistry. Monitoring and assessment of these parameter values is an integral part of establishing the quality of the water calculating Water Quality Index (WQI) establishing risk analysis on human health and developing of machine learning-based models for the prediction of these parameters [31-33]. Determination of groundwater quality is based on the continuously monitored parameters for the efficient management and control of contamination and for sustainable use of groundwater [33-35].

pH: pH is the degree of acidic and alkaline nature of water. The pH varies depending on the minerals content and chemical reaction in the aquifer. The value of the pH recommended by WHO (2022) [5] for drinking water is between 6.5 and 8.5 other wises scaling, corrosion or bad taste, variation of solubility of the metals, nutrients would occur in water.

Electrical conductivity (EC): EC gives an indication of the total amount of salts dissolved in water and is generally used to represent the complete mineralization of groundwater. High electrical conductivity values can be related to high salinity and mineralization levels and are usually caused by natural phenomena like weathering of rocks and man-made causes like discharge of industrial wastes, drain water from irrigation and infiltration of sea water [9,36].

Total dissolved solids (TDS): TDS refers to all the inorganic and organic constituents present in a solution. A high level of TDS in water causes water to taste unpleasant and renders it unfit for domestic, agricultural or industrial consumption. TDS in drinking water should preferably not exceed 500 mg/L as recommended [9].

Total hardness (TH): TH is most closely related to calcium and magnesium ions and will commonly form scale within pipes, appliances and equipment; also, in higher concentrations the effectiveness of soaps and detergents is decreased. The source of TH can be linked to the dissolution of carbonate rock such as in limestone or dolomite aquifers [37,38]. The status of groundwater should be checked for TH as water quality when in use:

Fluoride: In the groundwater, fluoride is found naturally due to weathering of fluoride bearing rocks through geological processes. The benefit of fluoride consumption in the optimum concentration is preventive tooth decay and dental diseases. In higher concentration, fluoride can cause dental fluorosis and skeletal fluorosis. The WHO recommended drinking water with 1.5 mg/L fluoride level is safe for drinking purposes [9,39].

Nitrate: Nitrate is one of the commonly found contaminants of groundwater in agriculture regions due to application of fertilizer for agriculture, livestock waste and sewage discharge. Excessive intake of nitrate concentration poses severe health risks to children, leading to methemoglobinemia, which is also termed as blue baby syndrome and the WHO guideline value of drinking water quality for nitrate is 50 mg/L [9,12,40].

Arsenic: Arsenic is one of the significant human induced health hazards, wherein groundwater acts as a source of drinking water. Chronic exposure to arsenic contaminated water could lead to skin lesions, cardiovascular diseases and several

cancer types. The WHO guideline value of arsenic concentration for drinking water is 0.01 mg/L [9,41,42].

Heavy metals: Various toxic heavy metals such as lead (Pb), cadmium (Cd), chromium (Cr), mercury (Hg), iron (Fe) and manganese (Mn) contamination in the groundwater through anthropogenic sources like industries, mining operations, agriculture and due to natural geological causes may contribute to health disorders such as neurological disorders, kidney diseases and carcinoma to human [37]. The examined parameters relevant to contaminant detection, water quality index (WQI) assessment, human health risk evaluation and machine learning (ML)-based prediction of groundwater quality are presented, providing essential information for evaluating groundwater suitability and supporting its safe and sustainable utilization [37,43].

Table-1 presents the key groundwater quality parameters along with their allowable limits and health or environmental implication. These parameters are considered to be the key determinants of the groundwater quality, assessment of contaminants and the predictors for the development of machine learning model.

GIS and remote sensing applications for groundwater quality assessment: GIS and remote sensing (RS) provide significant information in the study of groundwater quality assessment, contamination zones, sustainable water resources management. By means of acquisition, integration, interpretation, depiction of spatial information using GIS and RS technology, groundwater status can be explored and sound management plan can be devised by experts and researchers [19,20,46,47]. GIS provides a powerful method to store, analyze and interpret the groundwater quality information obtained from field survey, monitoring well and laboratory test. The spatial distribution of the groundwater quality parameters as well as their relationship with the other environment-logical, hydrological and geological data can be analyzed and hotspots contamination areas can be delineated and estimate its spatial extent at local and regional level [19,48-50]. Among the spatial interpolation methods widely used in groundwater research, inverse distance weighting (IDW), ordinary kriging, universal kriging and spline interpolation are commonly applied to estimate groundwater quality parameters at unsampled locations and generate continuous spatial distribution maps [20,46]. Remote sensing, conversely, presents land-use/land-cover conditions, land surface characteristics, vegetation vigor, potential ground water recharge zone, relation between surface water and ground water, all of which impact the ground water quality significantly. Landsat, Sentinel and MODIS satellite data are well established as sources for analysis of ground water resources and contamination issues over large areas [19,47,51,52]. Combining of remote sensing data with GIS based analysis would enhance the ground water vulnerability and contamination hazard mapping. Several studies related to groundwater quality were performed using GIS and Remote sensing techniques to detect contamination by different pollutants such as nitrate, fluoride, arsenic, seawater intrusion and heavy metals, to know about the vulnerability zones for further treatment, management or remediation activities [53-55]. The newest technologies have also improved studies on the quality of groundwater by the integration of GIS, RS with AI. The association of machine learning algorithm with geo-referenced information has assisted to estimate pollution hazard and identify polluted areas precisely and determine water vulnerability accurateness [18,56-58]. Such integrated methodologies have also extensively used in the smart water management plans to handle the massive data quickly in decision support system [18,56-58]. However, by and large GIS and remote sensing technologies are capable to act as a good tool to monitor the groundwater quality, mapping and analyzing the contamination risk, water management for the resources in a sustainable manner. Further enhancement of existing water management plan using future emerging technology and smart system like IoT along with GIS and remote sensing can also improve water management

Table-2 summarizes the major applications of GIS and remote sensing in groundwater quality assessment, emphasizing the role of spatial analysis, interpolation techniques, and satellite-derived observations in contaminant distribution mapping, groundwater vulnerability assessment and sustainable resource management.

Fig. 2 illustrates the GIS-based groundwater quality assessment framework, beginning with data collection and processing, followed by spatial interpolation, contamination mapping and decision support for groundwater management.

IoT-based groundwater monitoring systems: The implementation of the IoT into groundwater quality monitoring has transformed conventional sampling-based approaches by enabling continuous, real-time measurement of water quality parameters. Traditional monitoring relies on the collection of the groundwater samples and analyzing them in laboratories.

TABLE-1
LIST OF GROUNDWATER QUALITY INDICATORS, STANDARD PERMISSIBLE VALUES AND THEIR HEALTH IMPLICATIONS

Parameter	Unit	Permissible limit	Health/environmental significance	Ref.
pH	–	6.5-8.5	Controls acidity, alkalinity and contaminant mobility	[9,44]
Electrical conductivity (EC)	µS/cm	No specific limit	Indicates salinity and dissolved ionic content	[9]
Total dissolved solids (TDS)	mg/L	500	Affects taste and drinking water suitability	[9,44]
Total hardness (TH)	mg/L as $CaCO_3$	500	Causes scaling and affects domestic water use	[9,37,38]
Fluoride	mg/L	1.5	Excess exposure may cause dental and skeletal fluorosis	[9,39,45]
Nitrate	mg/L	50	High concentrations may cause methemoglobinemia	[9,12,40]
Arsenic	mg/L	0.01	Carcinogenic and associated with chronic health effects	[9,41,42]
Lead (Pb)	mg/L	0.01	Neurological and developmental disorders	[9,13,43]
Cadmium (Cd)	mg/L	0.003	Kidney damage and toxic effects	[9,13,43]
Chromium (Cr)	mg/L	0.05	Potential carcinogenic effects	[9,13,37]

TABLE-2
LIST OF GIS AND REMOTE SENSING TECHNOLOGIES, THEIR APPLICATIONS AND CORRESPONDING OUTPUTS IN GROUNDWATER QUALITY ASSESSMENT

Technology	Application	Output	Ref.
GIS	Groundwater quality mapping	Spatial distribution maps	[19,48,49]
GIS	Contamination hotspot identification	Risk maps	[20,50]
IDW	Spatial interpolation of groundwater parameters	Distribution maps	[20,46]
Ordinary kriging	Spatial prediction and uncertainty assessment	Continuous contamination surface	[20,46]
Remote sensing	Land-use and land-cover analysis	Pollution source identification	[47,48]
Landsat/sentinel imagery	Groundwater recharge and vulnerability assessment	Vulnerability maps	[19,47,52,55]
GIS + Machine learning	Groundwater contamination prediction	Intelligent decision-support systems	[18,57,58]
GIS + Remote sensing + AI	Integrated groundwater management	Risk assessment and monitoring framework	[18,54,56]

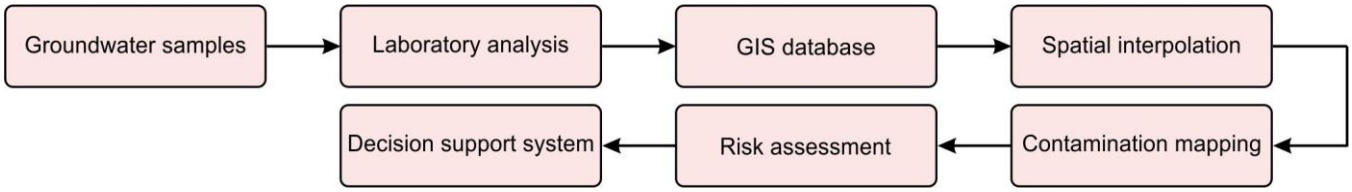


Fig. 2. Flow chart of GIS-based groundwater quality assessment framework

Although this approach provides accurate and reliable measurements, however, it is time-consuming, labour-intensive, and often unable to detect sudden changes in groundwater composition [21,22,56,59]. IoT-based systems automate data collection, transmission, storage and analysis, which improve the monitoring efficiency and data accessibility.

An IoT-based groundwater monitoring system typically comprises chemical sensors, microcontrollers, communication modules and cloud-based data processing platforms. Sensors measure physico-chemical parameters such as pH, electrical conductivity (EC), total dissolved solids (TDS), temperature, dissolved oxygen, and turbidity, alongside selected chemical contaminants such as nitrate and heavy metals. The measurements are transmitted to central servers through wireless communication technologies such as Wi-Fi, GSM, ZigBee, LoRaWAN and NB-IoT for subsequent processing and interpretation [21,22,60]. Proper sensor selection and calibration are necessary to maintain measurement accuracy, particularly for specific ions and potentially toxic elements.

Cloud-based platforms enable data storage, visualization and trend analysis, with automated alerts generated when water quality parameters exceed predefined thresholds. Integration of AI and ML models supports the detection of abnormal changes in hydrochemical parameters and the prediction of potential contamination events, allowing timely intervention [23,56,61]. Continuous data collection expands monitoring coverage, lowers operational costs and provides researchers, environmental authorities and policymakers with reliable information for informed groundwater management [60,62].

Integrating IoT with AI, GIS and remote sensing further strengthens groundwater monitoring by combining real-time measurements, predictive analysis and spatial assessment. Such integrated systems can identify unusual changes in water quality, estimate contamination risks and generate spatial distribution maps to locate potentially polluted groundwater sources. These capabilities offer considerable potential for intelligent water management and digital environmental monitoring [16,56,63]. Despite these advantages, the practical implementation of IoT-based groundwater monitoring faces challenges related to sensor calibration, maintenance, measurement accuracy, communication reliability, network coverage, power supply, cybersecurity and equipment costs. Current research focuses on developing cost-effective, durable sensors, energy-efficient monitoring devices, edge-computing systems and reliable data processing techniques to improve the accuracy, security and long-term performance of groundwater monitoring networks [60,64-66].

Table-3 summarizes the main components of IoT-based groundwater monitoring systems and their respective functions. The integration of sensors, communication networks, cloud computing and data analytics enables real-time monitoring and informed groundwater management. Fig. 3 presents the system architecture, covering data acquisition, wireless transmission, cloud storage, data processing and decision support.

TABLE-3
LIST OF ESSENTIAL HARDWARE AND SOFTWARE COMPONENTS USED IN IoT-BASED GROUNDWATER MONITORING

Component	Function	Examples	Ref.
Sensors	Measure water quality parameters	pH, EC, TDS, turbidity sensors	[21,22,60]
Microcontrollers	Data acquisition and processing	Arduino, ESP32, raspberry Pi	[21,23]
Communication modules	Data transmission	Wi-Fi, GSM, LoRaWAN, ZigBee	[21,22,60]
Cloud platforms	Data storage and analytics	AWS, Azure, Google Cloud	[23,56,61]
Analytics engine	Prediction and decision support	AI/ML models	[16,56,63]

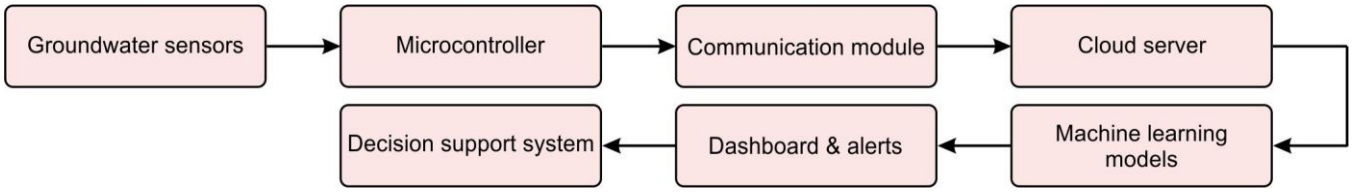


Fig. 3. Flow chart of IoT-based groundwater monitoring architecture

Machine learning (ML) models for groundwater quality prediction: ML is an effective approach for assessing groundwater quality and predicting contamination. These models use historical physico-chemical parameters, contaminant concentrations, water quality index (WQI) values and relevant environmental variables to predict groundwater quality and assess potential health risks [16,30,67]. Most of the traditional statistics have difficulty in managing the complex nonlinear relationship between the hydrogeology, environment and quality variables. However, machine learning could use the countless amounts of data to analyze, identify obscure patterns and build reliable predicted models for groundwater quality assessment [16,30,68]. Groundwater quality prediction utilizes the recorded values for physico-chemical parameters, contaminant concentrations, WQI and possible health risks on the basis of observed past and related environmental variables [16,18,69]. Enhanced availability of ground water monitoring data and computational power have led to the proliferation of machine learning algorithms for groundwater investigations [16,18,63].

Artificial neural networks (ANN): Among the different kinds of ML models that have been successfully used to predict groundwater quality (GWQ), ANNs are one of the most frequently used. ANNs are designed with inspiration from the structure of the human brain and have the ability to capture complex nonlinear relationships between groundwater quality parameters. Many investigations on using ANN for prediction of different parameters of GWQ such as pH, TDS, EC, fluoride, nitrate and WQI are available and most of them have achieved high prediction accuracy [56,67,70,71]. On the contrary to the high accuracy of the models, ANNs usually need big data size and enough computation time in order to train. However, overfitting and limited interpretability are the additional limitations, which must be addressed before applying these models to GWQ management [59,71].

Random forest (RF): RF is an ensemble learning technique that improves predictive accuracy and model robustness. It performs well with noisy and incomplete datasets and has been applied to groundwater contamination classification, water quality index (WQI) prediction, arsenic occurrence assessment and groundwater vulnerability mapping [57,58,72]. RF can estimate feature importance and help in identify the variables, which is the most strongly influence groundwater quality and supporting result interpretation. Compared with artificial neural networks (ANNs), RF generally requires less parameter tuning and offers a more transparent modelling process [72].

Support vector machines (SVM): SVM is a supervised learning algorithm widely used for classification and regression tasks. It is suitable for modelling high-dimensional and nonlinear data and has been applied to pollutant concentration prediction, groundwater suitability classification and water quality index (WQI) estimation [57,73,74]. SVM offers good generalization performance, resistance to overfitting when properly tuned and reliable predictions with small datasets [73]. Its limitations include sensitivity to kernel selection, the need for parameter optimization and high computational costs when processing large datasets [75].

Extreme gradient boosting (XGBoost): The XGBoost is an ensemble machine learning algorithm widely used for environmental prediction. It captures nonlinear relationships by sequentially correcting errors from previous iterations, often achieving high predictive accuracy in groundwater quality modelling [76-78]. Its key advantages include computational efficiency, the ability to handle missing values and feature selection through feature-importance analysis. These capabilities make XGBoost suitable for groundwater quality prediction, contamination assessment, water quality index (WQI) estimation and environmental risk assessment [78].

Deep learning models: Deep learning uses neural networks with multiple hidden layers to identify complex patterns in data. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks and hybrid CNN–LSTM models are increasingly used for groundwater quality prediction and spatiotemporal contamination assessment [68,79,80]. LSTM networks are particularly useful for time-series forecasting, as they can capture long-term dependencies in groundwater monitoring data. Deep learning models can achieve high predictive accuracy, although their performance depends on data availability, computational resources and careful hyperparameter tuning [79,80]. Hybrid CNN-LSTM models can capture spatial and temporal dependencies simultaneously, which improve the groundwater quality forecasting [68,79,80].

Comparative evaluation of machine learning models: The selection of an appropriate ML model depends on dataset size, required prediction accuracy, computational resources and interpretability. ANNs and deep learning models can capture complex nonlinear relationships, whereas RF and XGBoost offer a practical balance between predictive performance, computational efficiency and model interpretation. SVMs are suitable for relatively small datasets and classification tasks [72,73,78]. Ensemble and hybrid AI approaches have reported improved performance in groundwater quality prediction compared with individual models [67,71,77,81]. Integrating ML with GIS, RS and IoT can strengthen groundwater monitoring and assessment [16,18,56]. These methods support contamination prediction, WQI estimation and human health risk assessment. Model performance varies with data quality, hydrogeological conditions, spatial heterogeneity and para-

meter selection. Careful model selection, uncertainty analysis and independent validation are essential before applying ML models to groundwater management. Advances in intelligent technologies are expected to expand their role in environmental assessment and decision-making [16,68,69,71].

Table-4 compares machine learning models used for groundwater quality prediction, outlining their advantages, limitations and applications. Fig. 4 presents the workflow for developing and evaluating these models, while Fig. 5 illustrates their integration with GIS and IoT technologies for real-time groundwater monitoring, spatial analysis and management decisions.

AI-based health risk assessment: Continuous consumption of contaminated groundwater leads to the formation of various diseases like dental and skeletal fluorosis, methemoglobinemia, neurological diseases, cardiovascular diseases, kidney failure, various cancers, *etc*. [9,12,41,45]. Therefore, health-risk assessment has become an important part of groundwater quality assessment and public health management [31]. Traditional methods of health risk assessment consider concentration of the contaminant and human exposure in the calculation of non-carcinogenic risk (HQ, HI) and carcinogenic risk (CR). The health risk (non-carcinogenic) should be less than one (HQ < 1); otherwise, possible health effect is occurred. However, carcinogenic health risk (of specific compounds) must be less than the acceptable risk or a high carcinogenic risk would occur [82,83]. The effectiveness and accuracy of health risk assessment is considerably enhanced with the utilization of sophisticated approaches based on AI and ML. Health risk models have capacity to manage enormous volumes of water quality data, model non-linear relationship between water quality parameters and predict health risk more precisely as compared to conventional statistical models [16,84,85]. Machine learning methods, such as random forest, artificial neural networks, support vector machines and deep learning, have been applied to predict health risk indicators, classify pollution levels and identify population groups vulnerable to groundwater contamination [84-86]. AI combined with GIS and remote sensing applications could improve the spatial health risk assessment.

Using all the described methods, location and extent of contaminated water as well as health risks among populations are effectively identified, whereas health risk map provided using GIS is used by policy makers to prioritize risk management measures and to manage resources effectively [53,87,88]. In addition, IoT-based groundwater monitoring system has ability to provide simultaneous, real-time and *in situ* measurements on groundwater quality parameter. Integration of ML with this IoT system would allow an early health risk warning mechanism, which contribute to mitigating emerging health risks [16,56,60]. Nevertheless, there were limitations to the wide applicability of AI based health risk assessment such as data availability, quantity of uncertainties and AI model transparency have to be further improved. The application of explainable artificial intelligence (XAI) and an overall analysis of uncertainties, combined with health-risk assessment platform

TABLE-4
LIST OF COMMONLY USED MACHINE LEARNING ALGORITHMS WITH THEIR APPLICATIONS, STRENGTHS AND LIMITATIONS IN GROUNDWATER QUALITY PREDICTION

Model	Major Application	Advantages	Limitations	Ref.
ANN	WQI prediction, contaminant forecasting	Handles nonlinear relationships	Overfitting, less interpretable	[59,70,71]
Random forest	Classification, contamination prediction	High accuracy, feature importance analysis	Computationally intensive for large datasets	[57,58,72]
SVM	Classification and regression	Good performance with small datasets	Parameter sensitivity and kernel selection	[57,73,74]
XGBoost	Advanced prediction modeling	High predictive performance and feature selection	Model complexity	[76-78]
CNN	Spatial contamination analysis	Strong feature extraction capability	Requires large datasets	[68,79]
LSTM	Time-series forecasting	Captures temporal patterns effectively	High computational cost	[68,80]

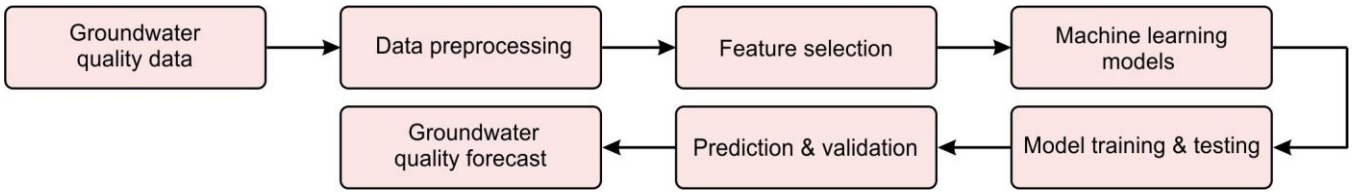


Fig. 4. Machine learning framework for groundwater quality prediction

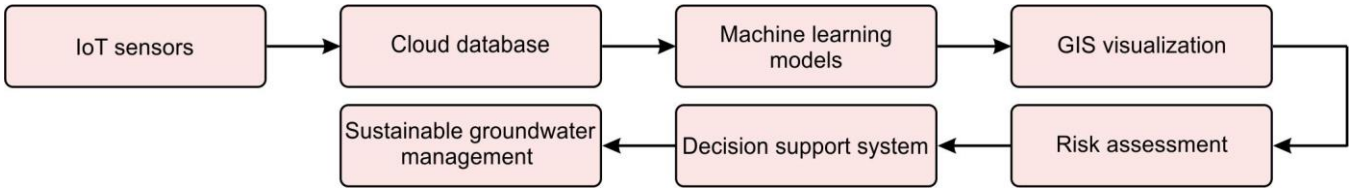


Fig. 5. Flow chart of Integration of AI, GIS and IoT for smart groundwater management

including environmental monitoring, machine learning, geospatial analysis *etc*., will ensure the reliability of the system and an effective decision-making can be implemented in future [16,89,90].

Table-5 summarizes major groundwater contaminants, their sources, associated health impacts and key risk indicators used in public health assessment. Building on these parameters, Fig. 6 presents a conceptual framework for AI-based groundwater health-risk assessment, linking groundwater quality monitoring with machine learning analysis, health risk estimation and decision support. This integrated approach supports the identification of contamination-related health hazards and helps prioritize interventions to protect vulnerable population groups.

Decision support systems (DSS) for smart groundwater management: Decision support systems play an important role in groundwater quality assessment, contamination management and sustainable water resource planning. They integrate data acquisition, storage, analysis, visualization and decision making tools to support policymakers, scientists and water resource managers in addressing complex groundwater problems [92-96]. Integrating AI, ML, GIS, RS and IoT into DSS enables large-scale monitoring data analysis, contamination trend assessment and groundwater quality prediction [56,60,94,97]. ML algorithms, such as ANN, RF, SVM and XGBoost, support the prediction of water quality parameters, WQI and contamination risks, which allow to authorities to plan timely interventions [16,30,76,94]. GIS-based maps identify contamination hotspots and vulnerable areas, which help to prioritize monitoring, remediation and resource allocation [53,58,98]. IoT networks provide continuous groundwater quality measurements, while cloud computing supports centralized data storage, processing and access across monitoring locations [56,60,61]. Key challenges include data integration, sensor reliability, cybersecurity, model uncertainty and interoperability among different technologies [65,89,99]. Addressing these limitations will strengthen AI-based DSS and support informed groundwater management and long-term water resource sustainability [56,60,94].

Table-6 outlines the key components of smart groundwater decision support systems and their functions. Fig. 7 shows their integration within a unified architecture, linking IoT-based data acquisition with the AI-driven analysis, GIS-

TABLE-5
LIST OF MAJOR GROUNDWATER CONTAMINANTS, THEIR SOURCES, ASSOCIATED HEALTH EFFECTS AND RISK ASSESSMENT INDICATORS

Contaminant	Major source	Health effects	Risk indicator	Ref.
Fluoride	Geological formations	Dental and skeletal fluorosis	HQ, HI	[9,45,88]
Nitrate	Fertilizers, sewage	Methemoglobinemia	HQ	[9,12,42,87]
Arsenic	Geogenic processes	Skin lesions, cancer	HQ, CR	[9,41,42,91]
Lead	Industrial discharge	Neurological disorders	HQ, CR	[9,13,37]
Cadmium	Mining, industrial waste	Kidney damage	HQ, CR	[9,13,43]
Chromium	Industrial effluents	Carcinogenic effects	CR	[9,13,16]

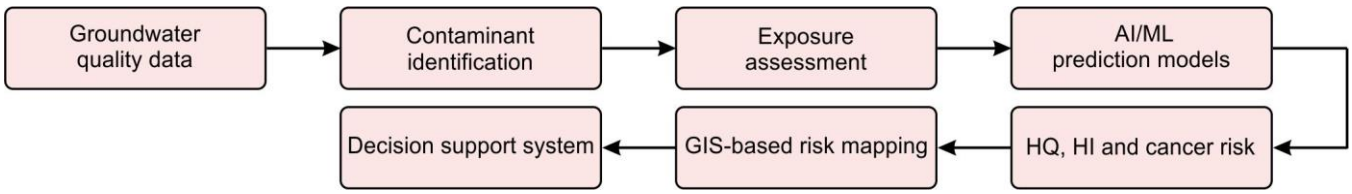


Fig. 6. Flow chart of AI-based health risk assessment framework

TABLE-6
LIST OF MAJOR COMPONENTS, THEIR FUNCTIONS AND RELATED TECHNOLOGIES IN SMART GROUNDWATER DECISION SUPPORT SYSTEMS

Component	Function	Technology	Ref.
Data acquisition	Continuous groundwater quality monitoring	IoT sensors	[21,22,56,60]
Data storage	Centralized data management and processing	Cloud computing	[56,61]
Data analysis	Groundwater quality prediction and assessment	Artificial intelligence and machine learning	[16,30,76,77]
Spatial analysis	Mapping, visualization and hotspot identification	GIS and remote sensing	[19,46,47,98]
Risk assessment	Contamination and health-risk evaluation	ML-Based risk models	[53,84,85]
Decision support	Sustainable groundwater management recommendations	Integrated DSS platforms	[92-96]

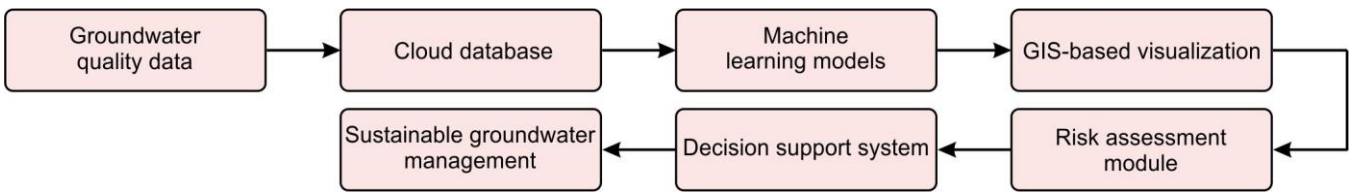


Fig. 7. Flow chart of smart groundwater decision support framework groundwater sensors (IoT)

based spatial visualization and cloud computing to support groundwater quality assessment, contamination management and sustainable resource planning.

Challenges and research gaps: Despite advances in AI, ML, GIS, RS and IoT for groundwater quality assessment and contamination prediction, several challenges limit their large-scale implementation. Addressing these issues is essential for developing reliable intelligent monitoring systems and sustainable groundwater management strategies. Data availability and quality remain major concerns for AI and ML applications. Groundwater monitoring data are often limited in many regions due to sparse monitoring networks, incomplete records, missing values, inconsistencies in sampling and data collection methods. These limitations can reduce model accuracy and prediction reliability, which affect the effectiveness of AI-based groundwater quality assessment systems [30,97,99].

Reliability and calibration of sensors: Water quality sensors in IoT-based groundwater monitoring networks enable continuous data acquisition, but their performance can be affected by calibration errors, sensor drift, environmental interference and device malfunction. These factors may compromise measurement accuracy and the reliability of subsequent predictions. Maintaining sensor stability over extended periods is particularly challenging in harsh environments and remote monitoring locations, where regular inspection and maintenance may be difficult. The development of robust, cost-effective and self-calibrating sensors is a key research priority for improving the accuracy and long-term reliability of groundwater monitoring systems [21,22,60].

Model interpretability: Although most of the high-performance ML and DL models excel at the prediction tasks, most of the state-of-the-art ML/DL systems function as "black-box" models, making them not very acceptable and usable for decision making. The requirements and necessity of having trustworthy AI-based water quality prediction and management system are increasingly becoming prominent, the predictions outputs are often unexplainable, Therefore, XAI technique is expected to overcome this limitation [89,90].

Model transferability: Although AI/ML models have shown promise in groundwater quality prediction, their transferability across different hydrogeological and climatic settings remains a major challenge. Models developed for a specific aquifer or region may lose predictive accuracy when applied to areas with different geological formations, land-use patterns, climatic conditions and pollution sources. Developing transferable models requires multi-region datasets, cross-validation across hydrogeological settings and domain adaptation techniques to improve performance in new environments.

Model reliability depends on appropriate data partitioning and validation strategies. Data leakage occurs when test data influence model training, preprocessing, feature selection or hyperparameter tuning, leading to overestimated predictive performance. Random data splitting may also provide misleading results when observations from nearby monitoring wells or repeated measurements from the same locations are divided between training and test sets. Spatially independent validation and chronological data splitting can provide a more realistic assessment of model performance at unobserved locations and during future periods. Overfitting remains a concern when datasets are small, incomplete or imbalanced. Regularization, control of model complexity and independent testing are important for evaluating predictive reliability. These methodological considerations help determine whether reported model accuracy represents genuine predictive capability and whether the models can be applied reliably across diverse groundwater systems.

Challenges in integration: Integrating AI, GIS, RS, IoT, cloud computing and decision support systems remains challenging due to differences in communication protocols, data formats, software architectures and computational requirements. Developing standardized, interoperable frameworks is essential for seamless data exchange, efficient processing and reliable integration of these technologies in intelligent groundwater monitoring and management systems [56,61,99].

Security and privacy concerns: Cloud-based platforms and large volumes of data generated by IoT sensors pose significant cybersecurity and privacy challenges in groundwater monitoring systems. Data breaches, unauthorized access and network vulnerabilities may compromise sensitive water quality information and undermine management decisions. Strong encryption, secure communication protocols, access controls, regular security audits and reliable data storage mechanisms are essential to protect monitoring networks and maintain the integrity and confidentiality of groundwater data [61,65].

Real-time decision support systems: Most of the existing groundwater quality monitoring systems focus on data collection, storage, retrieval and visualization, with limited capabilities for real-time automated decision-making and interactive resource management. Developing intelligent decision support systems that integrate continuous monitoring, predictive analytics, automated alerts and timely management recommendations remains an important research priority [92-94].

Research gaps: The literature review identifies several research gaps that need to be addressed to improve groundwater quality monitoring and management: (i) limited integration of AI, GIS, RS, and IoT within unified monitoring frameworks; (ii) insufficient application of explainable artificial intelligence (XAI) to improve the interpretability of groundwater quality predictions; (iii) inadequate real-time monitoring networks capable of supporting large-scale applications; (iv) limited investigation of Digital Twins for groundwater modelling, simulation and management; (v) insufficient integration of uncertainty quantification methods such as Bayesian modelling, Monte Carlo simulation, ensemble modelling and probabilistic forecasting, to assess prediction reliability; (vi) inadequate attention to cybersecurity and data privacy in smart water management systems; and (vii) limited use of edge computing for local data processing and real-time assessment. Federated learning offers another potential approach for collaborative model development across monitoring networks while limiting the need to centralize sensitive data [66,89,90,100-103]. Table-7 shows the major research challenges and limitations in smart groundwater monitoring and management, which identify the priority areas for developing reliable, scalable and efficient intelligent groundwater management systems.

Future research directions: Advances in AI, ML, GIS, RS and IoT are expected to strengthen future groundwater quality monitoring and management. Integrated intelligent

TABLE-7
LIST OF MAJOR CHALLENGES, THEIR IMPACTS, AND FUTURE RESEARCH NEEDS IN SMART GROUNDWATER MANAGEMENT

Challenge	Impact	Future research need	Ref.
Data scarcity	Reduced prediction accuracy	Large-scale monitoring databases	[30,97,99]
Sensor reliability	Poor data quality	Self-calibrating sensors	[21,22,60]
Black-box AI models	Limited trust and adoption	Explainable AI (XAI)	[89,90]
Technology integration	Interoperability issues	Unified frameworks	[56,61,99]
Cybersecurity	Data vulnerability	Secure IoT architecture	[65]
Limited DSS capability	Delayed decisions	Real-time intelligent DSS	[92-94]
Prediction uncertainty	Reduced reliability of AI predictions	Uncertainty quantification frameworks	[89,90]
Real-time processing limitations	Delayed contamination response	Edge computing integration	[66]
Decentralized data management	Data privacy concerns	Federated learning approaches	[102,103]
Lack of virtual groundwater systems	Limited scenario analysis capability	Digital twin development	[100,101]

systems are needed to support real-time monitoring, contamination forecasting, health-risk assessment and informed decision making for sustainable groundwater resource management [56,60,92,94]. Several emerging technologies offer potential solutions to current limitations, although their practical effectiveness requires further investigation.

Explainable artificial intelligence (XAI) is a promising research direction for improving the interpretability of ML models used in groundwater quality assessment. By identifying the contribution of input variables to model predictions, XAI can help researchers and groundwater managers understand the factors influencing groundwater quality. Its reliability must be assessed using suitable explanation methods and groundwater-specific validation [89,90]. Digital Twin technology offers another potential approach through the creation of virtual representations of groundwater systems. Integrating Digital Twins with IoT sensor networks, GIS databases and ML algorithms could support real-time simulation, contamination forecasting, scenario analysis and adaptive groundwater management [100,101].

Future research should focus on validating these frameworks across different aquifer types and hydrogeological settings. Linking real-time sensor observations with groundwater flow and contaminant transport models could improve the simulation of groundwater conditions and the prediction of contamination events. Scenario-based simulations may help evaluate groundwater abstraction strategies, pollution control measures, and remediation options. Reliable implementation will depend on sensor data quality, interoperability, model calibration, computational requirements and validation against field observations. Quantifying predictive uncertainty under changing climatic and environmental conditions is essential for assessing model reliability. Validated Digital Twin systems could support early-warning mechanisms, infrastructure maintenance, and evidence-based groundwater policy decisions [100,101].

Edge computing offers opportunities to process monitoring data close to the point of collection, reducing communication delays and supporting timely assessment of groundwater quality. Its suitability depends on device capabilities, computational resources, network connectivity and the reliability of locally generated predictions [66]. Federated learning provides a potential framework for combined model development when groundwater data are distributed across institutions and cannot readily be shared. Although this approach reduces the need to transfer raw data, its effectiveness depends on data compatibility, communication requirements, model performance across participating locations and appropriate privacy safeguards. The groundwater-specific studies are needed to establish its practical benefits and limitations [102,103].

Future research should prioritize unified AI-GIS-IoT platforms that integrate real-time sensor data, spatial analysis, machine-learning predictions, cloud computing and decision support. Such platforms could improve contamination forecasting, identify the targeted and vulnerable areas and remediation [56,61,98]. Smart city and smart village initiatives should incorporate groundwater quality monitoring into their environmental management programmes through sensor networks, cloud-based platforms, geospatial tools and AI-driven forecasting [56,60,61]. Achieving these objectives will require collaboration among hydrologists, geologists, environmental engineers, computer scientists, data analysts and policymakers. Field-based validation of integrated systems is essential to establish their reliability, scalability and contribution to sustainable groundwater management [100-103].

Table-8 summarizes emerging technologies and future research opportunities in groundwater quality monitoring and management, with emphasis on improving prediction accu-

TABLE-8
LIST OF EMERGING TECHNOLOGIES AND FUTURE RESEARCH OPPORTUNITIES

Emerging technology	Potential application	Expected benefit	Ref.
Explainable AI (XAI)	Model interpretation	Improved transparency	[89,90]
Digital Twins	Virtual groundwater systems	Real-time simulation	[100,101]
Edge computing	Local data processing	Reduced latency	[66]
Federated learning	Distributed AI modeling	Data privacy protection	[102,103]
Smart IoT networks	Continuous monitoring	Real-time assessment	[21,22,60]
AI–GIS–IoT integration	Intelligent groundwater management	Enhanced decision support	[56,61,98]
Digital Twin + AI integration	Predictive groundwater simulation	Improved planning and management	[100,101]
Edge-AI systems	Real-time contamination detection	Faster response and reduced latency	[66,102]

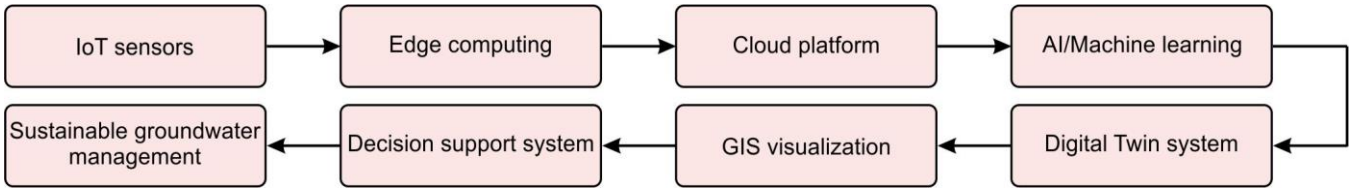


Fig. 8. Flow chart of future intelligent groundwater management framework

TABLE-9
LIST OF COMPARATIVE SUMMARIES OF REVIEWED TECHNOLOGIES

Technology	Strengths	Limitations	Major applications	Ref.
GIS	Effective spatial analysis and mapping	Depends on quality of spatial data	Groundwater quality mapping, vulnerability assessment	[19,20,46]
Remote sensing	Large-area coverage and rapid assessment	Indirect measurement of groundwater conditions	Land-use analysis, recharge assessment, contamination mapping	[47,52,55]
Artificial neural networks (ANN)	Handles complex nonlinear relationships	Overfitting, limited interpretability	WQI prediction, groundwater quality forecasting	[59,71,75]
Random forest (RF)	High accuracy and feature importance analysis	Computationally intensive for large datasets	Contamination prediction, groundwater potential mapping	[57,58,72]
Support vector machine (SVM)	Effective with small and high-dimensional datasets	Sensitive to kernel and parameter selection	Classification and regression of groundwater quality	[73,74]
XGBoost	High predictive performance and robustness	Model complexity and tuning requirements	Water quality prediction and contamination assessment	[76-78]
Deep learning (CNN/LSTM)	Captures spatial and temporal patterns	Requires large datasets and high computational power	Time-series forecasting and contamination prediction	[68,79,80]
IoT	Real-time monitoring and automated data collection	Sensor maintenance and communication issues	Smart groundwater monitoring systems	[21,22,60]
AI–GIS–IoT integration	Comprehensive intelligent groundwater management	Integration and interoperability challenges	Decision support, risk assessment, smart monitoring	[16,18,56]

racy, model transparency, real-time monitoring and decision making. Fig. 8 presents a future-oriented framework integrating AI, GIS, IoT, Digital Twins, edge computing and federated learning for intelligent groundwater monitoring and sustainable resource management. Table-9 compares the principal technologies reviewed in this study, outlining their strengths, limitations and major applications in groundwater quality monitoring, contamination forecasting and intelligent management.

Conclusions

Groundwater quality is under growing pressure from urbanization, industrial activities, agricultural expansion, and climate change, creating a need for more efficient monitoring and management approaches. Conventional sampling and laboratory analysis remain important, but their cost, limited monitoring coverage and lack of predictive capability restrict their effectiveness for large-scale and continuous assessment. This review examines the role of AI, ML, GIS, RS and IoT in advancing groundwater quality monitoring, contamination forecasting, health-risk assessment and resource management. Geospatial technologies support the identification of contamination hotspots and vulnerable areas, while ML models such as ANN, RF, SVM, XGBoost and deep learning help predict groundwater quality parameters, water quality indices and contamination risks. IoT-based sensor networks enable continuous data collection and timely alerts, while the integration of these technologies offers a practical foundation for intelligent groundwater management. The widespread application of these systems remains constrained by inadequate datasets, sensor reliability issues, limited model transparency, uncertainty in predictions, cybersecurity risks and difficulties in integrating technologies across different scales. Research on XAI, Digital Twins, edge computing, federated learning, and integrated AI–GIS–IoT platforms may help address these limitations. Future efforts should prioritize field validation, standardized data practices, model reliability and practical implementation under diverse hydrogeological conditions. This review provides a consolidated understanding of current technological developments, their applications and unresolved challenges. The insights can guide researchers, environmental agencies, engineers and policymakers in designing effective groundwater monitoring programmes and developing evidence based management strategies to protect groundwater quality and ensure the long-term sustainability of this essential resource.

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CONFLICT OF INTEREST

The authors declare that there is no conflicts of interest regarding the publication of this article.

DECLARATION OF AI-ASSISTED TECHNOLOGIES

During the preparation of this manuscript, the authors used an AI-assisted tool(s) to improve the language and no

data, results or scientific conclusions were generated by AI. All analyses, interpretations and conclusions are the authors' own. The authors reviewed and edited the content and take full responsibility for the published work.

REFERENCES

1. U. Lall, L. Josset and T. Russo, *Annu. Rev. Environ. Resour.*, **45**, 171 (2020); https://doi.org/10.1146/annurev-environ-102017-025800
2. T. Gleeson, Y. Wada, M.F.P. Bierkens and L.P.H. van Beek, *Nature*, **488**, 197 (2012); https://doi.org/10.1038/nature11295
3. R. Taylor, B. Scanlon, P. Döll, M. Rodell, R. van Beek, M. Leblanc, L. Longuevergne, Y. Wada, J.S. Famiglietti, M. Edmunds, L. Konikow, T.R. Green, J. Chen, M. Taniguchi, M.F.P. Bierkens, A. MacDonald, Y. Fan, R.M. Maxwell, Y. Yechieli, J.J. Gurdak, M. Shamsudduha, D.M. Allen, K. Hiscock, P.J.-F. Yeh, I. Holman and H. Treidel, *Nat. Clim. Chang.*, **3**, 322 (2013); https://doi.org/10.1038/nclimate1744
4. J. Famiglietti, *Nat. Clim. Chang.*, **4**, 945 (2014); https://doi.org/10.1038/nclimate2425
5. M. Giordano, *Annu. Rev. Environ. Resour.*, **34**, 153 (2009); https://doi.org/10.1146/annurev.environ.030308.100251
6. Y. Wada, L.P.H. van Beek, C.M. van Kempen, J.W.T.M. Reckman, S. Vasak and M.F.P. Bierkens, *Geophys. Res. Lett.*, **37**, 2010GL044571 (2010); https://doi.org/10.1029/2010GL044571
7. X. Xie, J. Shi, K. Pi, Y. Deng, B. Yan, L. Tong, L. Yao, Y. Dong, J. Li, L. Ma and C. Zheng, *Annu. Rev. Environ. Resour.*, **48**, 395 (2023); https://doi.org/10.1146/annurev-environ-112321-114701
8. Y. Zhang and P. Li, *Environ. Sci. Pollut. Res. Int.*, **30**, 51234 (2023); https://doi.org/10.1007/s11356-023-26000-0
9. Y. Jurczynski, R. Passos and L.C. Campos, *Sustainability*, **16**, 7107 (2024); https://doi.org/10.3390/su16167107
10. D.J. Lapworth, N. Baran, M.E. Stuart and R.S. Ward, *Environ. Pollut.*, **163**, 287 (2012); https://doi.org/10.1016/j.envpol.2011.12.034
11. M.E. Stuart, D.J. Lapworth, E.J. Crane and A. Hart, *Sci. Total Environ.*, **416**, 1 (2012); https://doi.org/10.1016/j.scitotenv.2011.11.072
12. M.H. Ward, R.R. Jones, J.D. Brender, T.M. de Kok, P.J. Weyer, B.T. Nolan, C.M. Villanueva and S.G. van Breda, *Int. J. Environ. Res. Public Health*, **15**, 1557 (2018); https://doi.org/10.3390/ijerph15071557
13. Y. Aryan, T. Pon, B. Panneerselvam and A.K. Dikshit, *J. Water Health*, **22**, 235 (2024); https://doi.org/10.2166/wh.2023.082
14. R. Rojas, L. Feyen and A. Dassargues, *Water Resour. Res.*, **44**, W12418 (2008); https://doi.org/10.1029/2008WR006908
15. M. Sophocleous, *Hydrogeol. J.*, **10**, 52 (2002); https://doi.org/10.1007/s10040-001-0170-8
16. M.S. Hanoon, A.N. Ahmed, C.M. Fai, A.H. Birima, A. Razzaq, M. Sherif, A. Sefelnasr and A. El-Shafie, *Water Air Soil Pollut.*, **232**, 411 (2021); https://doi.org/10.1007/s11270-021-05311-z
17. S. Singha, S. Pasupuleti, S.S. Singha, R. Singh and S. Kumar, *Chemosphere*, **276**, 130265 (2021); https://doi.org/10.1016/j.chemosphere.2021.130265
18. B. Rammohan, P. Partheeban, R. Ranganathan and S. Balaraman, *Sustainability*, **16**, 9848 (2024); https://doi.org/10.3390/su16229848
19. M.K. Jha, V.M. Chowdary and A. Chowdhury, *Hydrogeol. J.*, **18**, 1713 (2010); https://doi.org/10.1007/s10040-010-0631-z
20. P.P. Adhikary, C.J. Dash, H. Chandrasekharan, T.B.S. Rajput and S.K. Dubey, *Arab. J. Geosci.*, **5**, 1423 (2012); https://doi.org/10.1007/s12517-011-0330-7
21. M.V. Storey, B. van der Gaag and B.P. Burns, *Water Res.*, **45**, 741 (2011); https://doi.org/10.1016/j.watres.2010.08.049
22. Z. Rasin and M.R. Abdullah, *IACSIT Int. J. Eng. Technol.*, **9**, 24 (2009).
23. R.W. Gullick, *J. AWWA*, **95**, 58 (2003); https://doi.org/10.1002/j.1551-8833.2003.tb10493.x
24. M.J. Page, J.E. McKenzie, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, L. Shamseer, J.M. Tetzlaff, E.A. Akl, S.E. Brennan, R. Chou, J. Glanville, J.M. Grimshaw, A. Hróbjartsson, M.M. Lalu, T. Li, E.W. Loder, E. Mayo-Wilson, S. McDonald, L.A. McGuinness, L.A. Stewart, J. Thomas, A.C. Tricco, V.A. Welch, P. Whiting and D. Moher, *BMJ*, **372**, n71 (2021); https://doi.org/10.1136/bmj.n71
25. D. Moher, A. Liberati, J. Tetzlaff, D.G. Altman, The PRISMA Group, *PLoS Med.*, **6**, e1000097 (2009); https://doi.org/10.1371/journal.pmed.1000097
26. B. Kitchenham and S. Charters, Guidelines for Performing Systematic Literature Reviews in Software Engineering, EBSE Technical Report EBSE-2007-001, Keele University and Durham University (2007).
27. H. Snyder, *J. Bus. Res.*, **104**, 333 (2019); https://doi.org/10.1016/j.jbusres.2019.07.039
28. Y. Xiao and M. Watson, *J. Plann. Educ. Res.*, **39**, 93 (2019); https://doi.org/10.1177/0739456X17723971
29. R.J. Torraco, *Hum. Resour. Dev. Rev.*, **15**, 404 (2016); https://doi.org/10.1177/1534484316671606
30. A. Mosavi, P. Ozturk and K. Chau, *Water*, **10**, 1536 (2018); https://doi.org/10.3390/w10111536
31. F. Chen, L. Yao, G. Mei, Y. Shang, F. Xiong and Z. Ding, *Water*, **13**, 783 (2021); https://doi.org/10.3390/w13060783
32. L. Pei-Yue, Q. Hui and W. Jian-Hua, *J. Chem.*, **7**, 451304 (2010); https://doi.org/10.1155/2010/451304
33. M. Bahir, S. Ouhamdouch, D. Ouazar and A. Chehbouni, *Carbonates Evaporites*, **35**, 27 (2020); https://doi.org/10.1007/s13146-020-00564-x
34. A. Nayak, G. Matta and D.P. Uniyal, *Environ. Dev. Sustain.*, **25**, 14229 (2022); https://doi.org/10.1007/s10668-022-02661-4
35. P. Li, J. Wu and H. Qian, *Earth Sci. Res. J.*, **18**, 27 (2014); https://doi.org/10.15446/esrj.v18n1.34048
36. B. Sarkar, A. Islam and A. Majumder, *Regional Stud. Marine Sci.*, **44**, 101751 (2021); https://doi.org/10.1016/j.rsma.2021.101751
37. S. He and J. Wu, *Expo. Health*, **11**, 125 (2019); https://doi.org/10.1007/s12403-018-0289-7
38. S. Akram and F. Rehman, *J. Chem. Appl.*, **4**, 4 (2018).
39. Y.S. Solanki, M. Agarwal, A.B. Gupta, S. Gupta and P. Shukla, *Sci. Total Environ.*, **807**, 150601 (2022); https://doi.org/10.1016/j.scitotenv.2021.150601
40. R.F. Spalding and M.E. Exner, *J. Environ. Qual.*, **22**, 392 (1993); https://doi.org/10.2134/jeq1993.00472425002200030002x
41. J. Podgorski and M. Berg, *Science*, **368**, 845 (2020); https://doi.org/10.1126/science.aba1510
42. P.L. Smedley and D.G. Kinniburgh, *Appl. Geochem.*, **17**, 517 (2002); https://doi.org/10.1016/S0883-2927(02)00018-5
43. M. Jaishankar, T. Tseten, N. Anbalagan, B.B. Mathew and K.N. Beeregowda, *Interdiscip. Toxicol.*, **7**, 60 (2014); https://doi.org/10.2478/intox-2014-0009
44. S. Pandey, G. Mohapatra and R. Arora, *J. Clean. Prod.*, **427**, 139149 (2023); https://doi.org/10.1016/j.jclepro.2023.139149
45. S. Li, Y. Wei, J. Zhou, Y. Li, L. Qiao, D. You, Y. Jiang, Z. Jiang, X. Wei, and X. Ma, *Cell Rep. Med.*, **7**, 102588 (2026); https://doi.org/10.1016/j.xcrm.2026.102588
46. P.K. Srivastava, D. Han, M. Gupta and S. Mukherjee, *Hydrol. Sci. J.*, **57**, 1453 (2012); https://doi.org/10.1080/02626667.2012.716156
47. A. Chowdhury, M.K. Jha, V.M. Chowdary and B.C. Mal, *Int. J. Remote Sens.*, **30**, 231 (2009); https://doi.org/10.1080/01431160802270131

48. S.S. Asadi, P. Vuppala and M.A. Reddy, *Int. J. Environ. Res. Public Health*, **4**, 45 (2007); https://doi.org/10.3390/ijerph2007010008
49. J. Krishnamurthy, A. Mani, V. Jayaraman and M. Manivel, *Int. J. Remote Sens.*, **17**, 1867 (1996); https://doi.org/10.1080/01431169608948744
50. E. Sener, A. Davraz and M. Ozcelik, *Hydrogeol. J.*, **13**, 826 (2005); https://doi.org/10.1007/s10040-004-0378-5
51. A. Jasrotia, A. Kumar and R. Singh, *Arab. J. Geosci.*, **9**, 304 (2016); https://doi.org/10.1007/s12517-016-2326-9
52. N.S. Magesh, N. Chandrasekar and J.P. Soundranayagam, *Geoscience Front.*, **3**, 189 (2012); https://doi.org/10.1016/j.gsf.2011.10.007
53. A. Rashid, M. Ayub, Z. Ullah, A. Ali, T. Sardar, J. Iqbal, X. Gao, J. Bundschuh, C. Li, S.A. Khattak, L. Ali, H.A. El-Serehy, P. Kaushik and S. Khan, *Int. J. Environ. Res. Public Health*, **20**, 2113 (2023); https://doi.org/10.3390/ijerph20032113
54. O. Rahmati, A. Nazari Samani, M. Mahdavi, H.R. Pourghasemi and H. Zeinivand, *Arab. J. Geosci.*, **8**, 7059 (2015); https://doi.org/10.1007/s12517-014-1668-4
55. H.-F. Yeh, Y.-S. Cheng, H.-I. Lin and C.-H. Lee, *Sustain. Environ. Res.*, **26**, 33 (2016); https://doi.org/10.1016/j.serj.2015.09.005
56. S.R. Krishnan, M.K. Nallakaruppan, R. Chengoden, M. Iyapparaja, S. Koppu, J. Sadhasivam and S. Sethuraman, *Sustainability*, **14**, 13384 (2022); https://doi.org/10.3390/su142013384
57. S.A. Naghibi, K. Ahmadi and A. Daneshi, *Water Resour. Manage.*, **31**, 2761 (2017); https://doi.org/10.1007/s11269-017-1660-3
58. S.A. Naghibi, H.R. Pourghasemi and B. Dixon, *Environ. Monit. Assess.*, **188**, 44 (2016); https://doi.org/10.1007/s10661-015-5049-6
59. H.R. Maier and G.C. Dandy, *Environ. Model. Softw.*, **15**, 101 (2000); https://doi.org/10.1016/S1364-8152(99)00007-9
60. C.Z. Zulkifli, S. Garfan, M. Talal, A.H. Alamoodi, A. Alamleh, I.Y.Y. Ahmaro, S. Sulaiman, A.B. Ibrahim, B.B. Zaidan, A.R. Ismail, O.S. Albahri, A.S. Albahri, C.F. Soon, N.H. Harun and H.H. Chiang, *Water*, **14**, 3621 (2022); https://doi.org/10.3390/w14223621
61. R. Buyya, C.S. Yeo, S. Venugopal, J. Broberg and I. Brandic, *Future Gener. Comput. Syst.*, **25**, 599 (2009); https://doi.org/10.1016/j.future.2008.12.001
62. J.O. Ighalo, A.G. Adeniyi and G. Marques, Internet of Things for Water Quality Monitoring and Assessment: A Comprehensive Review, In: Artificial Intelligence for Sustainable Development: Theory, Practice and Future Applications, Studies in Computational Intelligence, Cham, Switzerland: Springer, vol. 912, pp. 245-259 (2021).
63. M. Shaikh and F. Birajdar, *Int. J. Sci. Res. Arch.*, **11**, 502 (2024); https://doi.org/10.30574/ijsra.2024.11.1.0105
64. M.E.E. Alahi and S.C. Mukhopadhyay, *Sensors*, **17**, 1885 (2017); https://doi.org/10.3390/s17081885
65. S. Sicari, A. Rizzardi, L.A. Grieco and A. Coen-Porisini, *Comput. Netw.*, **76**, 146 (2015); https://doi.org/10.1016/j.comnet.2014.11.008
66. W. Shi, J. Cao, Q. Zhang, Y. Li and L. Xu, *IEEE Internet Things J.*, **3**, 637 (2016); https://doi.org/10.1109/JIOT.2016.2579198
67. V. Nourani, M. Alami and M. Aminfar, *Eng. Appl. Artif. Intell.*, **22**, 466 (2009); https://doi.org/10.1016/j.engappai.2008.09.003
68. F. Sham, A. El-Shafie, W.Z.B.W. Jaafar, S. Adarsh and A.N. Ahmed, *Arch. Comput. Methods Eng.*, **32**, 3593 (2025); https://doi.org/10.1007/s11831-025-10248-1
69. E.A. Hussein, C. Thron, M. Ghaziasgar, A. Bagula and M. Vaccari, *Algorithms*, **13**, 300 (2020); https://doi.org/10.3390/a13110300
70. P. Coulibaly, F. Anctil and B. Bobée, *J. Hydrol. Eng.*, **6**, 367 (2001); https://doi.org/10.1061/(ASCE)1084-0699(2001)6:5(367)
71. T. Rajaee, H. Ebrahimi and V. Nourani, *J. Hydrol.*, **572**, 336 (2019); https://doi.org/10.1016/j.jhydrol.2018.12.037
72. L. Breiman, *Mach. Learn.*, **45**, 5 (2001); https://doi.org/10.1023/A:1010933404324
73. V.N. Vapnik, Introduction: Four Periods in the Research of the Learning Problem, In: The Nature of Statistical Learning Theory, Statistics for Engineering and Information Science. New York, NY, USA: Springer, pp. 1-15 (2000).
74. O. Kisi and K.S. Parmar, *J. Hydrol.*, **534**, 104 (2016); https://doi.org/10.1016/j.jhydrol.2015.12.014
75. I.N. Daliakopoulos, P. Coulibaly and I.K. Tsanis, *J. Hydrol.*, **309**, 229 (2005); https://doi.org/10.1016/j.jhydrol.2004.12.001
76. M. Akhlaq, A. Ellahi, R. Niaz, M. Khan, S.S. Sammen and M. Scholz, *Tellus, Ser. A, Dyn. Meterol. Oceanogr.*, **76**, 177 (2024); https://doi.org/10.16993/tellusa.4069
77. A. Elmotawakkil, N. Enneya, S. Bhagat, M. Ouda and V. Kumar, *J. Hydroinform.*, **27**, 299 (2025); https://doi.org/10.2166/hydro.2025.290
78. T. Chen and C. Guestrin, XGBoost: A Scalable Tree Boosting System; In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining Association for Computing Machinery, pp. 785-794 (2016); https://doi.org/10.1145/2939672.2939785
79. Y. LeCun, Y. Bengio and G. Hinton, *Nature*, **521**, 436 (2015); https://doi.org/10.1038/nature14539
80. S. Hochreiter and J. Schmidhuber, *Neural Comput.*, **9**, 1735 (1997); https://doi.org/10.1162/neco.1997.9.8.1735
81. V. Sehgal, M.K. Tiwari and C. Chatterjee, *Water Resour. Manage.*, **28**, 2793 (2014); https://doi.org/10.1007/s11269-014-0638-7
82. United States Environmental Protection Agency, Risk Assessment Guidance for Superfund (RAGS): Volume I-Human Health Evaluation Manual (Part E), U.S. Environmental Protection Agency: Washington, DC, USA (2004).
83. United States Environmental Protection Agency, Risk Assessment Guidance for Superfund (RAGS): Volume I-Human Health Evaluation Manual (Part F): Supplemental Guidance for Inhalation Risk Assessment, U.S. Environmental Protection Agency: Washington, DC, USA (2011).
84. A. Mohammadpour, E. Gharehchahi, M. Golaki, M. Gharaghani, F. Ahmadian, S. Abolfathi, M. Samaei, M.G. Uddin, A. Olbert and A. Mousavi Khaneghah, *Results Eng.*, **27**, 105421 (2025); https://doi.org/10.1016/j.rineng.2025.105421
85. M.G. Uddin, M. Imran, A. Sajib, M. Hasan, M.T. Diganta, T. Dabrowski, A. Olbert and M. Moniruzzaman, *J. Contam. Hydrol.*, **261**, 104307 (2024); https://doi.org/10.1016/j.jconhyd.2024.104307
86. J. Chen, H. Gui, Y. Guo and J. Li, *Int. J. Environ. Res. Public Health*, **19**, 12000 (2022); https://doi.org/10.3390/ijerph191912000
87. J. Iqbal, C. Su, M. Wang, H. Abbas, M.Y.J. Baloch, J. Ghani, Z. Ullah and M.E. Huq, *Environ. Sci. Pollut. Res. Int.*, **30**, 61606 (2023); https://doi.org/10.1007/s11356-023-25958-x
88. A. Narsimha and V. Sudarshan, *Appl. Water Sci.*, **7**, 2717 (2016); https://doi.org/10.1007/s13201-016-0489-x
89. A.B. Arrieta, N. Díaz-Rodríguez, J. Del Ser, A. Bennetot, S. Tabik, A. Barbado, S. García, S. Gil-López, D. Molina, R. Benjamins, R. Chatila and F. Herrera, *Inf. Fusion*, **58**, 82 (2020); https://doi.org/10.1016/j.inffus.2019.12.012
90. M.T. Ribeiro, S. Singh and C. Guestrin, Why should I trust you?: Explaining the Predictions of any Classifier; In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1135-1144 (2016); https://doi.org/10.1145/2939672.2939778.
91. H. Brammer and P. Ravenscroft, *Environ. Int.*, **35**, 647 (2009); https://doi.org/10.1016/j.envint.2008.10.004
92. D.J. Power, Decision Support Systems: Concepts and Resources for Managers, Greenwood Publishing Group (2002).
93. J.P. Shim, M. Warkentin, J.F. Courtney, D.J. Power, R. Sharda and C. Carlsson, *Decis. Support Syst.*, **33**, 111 (2002); https://doi.org/10.1016/S0167-9236(01)00139-7

94. E. Turban, R. Sharda, D. Delen and D. King, Decision Support and Business Intelligence Systems, Pearson, edn 9 (2011).
95. P.G.W. Keen and M.S. Scott Morton, Decision Support Systems: An Organizational Perspective, Addison-Wesley (1978).
96. R.H. Sprague and E.D. Carlson, Building Effective Decision Support Systems, Prentice Hall (1982).
97. A. Halevy, P. Norvig and F. Pereira, *IEEE Intell. Syst.*, **24**, 8 (2009); https://doi.org/10.1109/MIS.2009.36
98. J. Malczewski, *Int. J. Geogr. Inf. Sci.*, **20**, 703 (2006); https://doi.org/10.1080/13658810600661508
99. C. Batini, C. Cappiello, C. Francalanci and A. Maurino, *ACM Comput. Surv.*, **41**, 1 (2009); https://doi.org/10.1145/1541880.1541883
100. F. Tao, H. Zhang, A. Liu and A.Y.C. Nee, *IEEE Trans. Ind. Inform.*, **15**, 2405 (2019); https://doi.org/10.1109/TII.2018.2873186
101. A. Fuller, Z. Fan, C. Day and C. Barlow, *IEEE Access*, **8**, 108952 (2020); https://doi.org/10.1109/ACCESS.2020.2998358
102. B. McMahan, E. Moore, D. Ramage, S. Hampson and B.A. y Arcas, Communication-Efficient Learning of Deep Networks from Decentralized Data, Proceedings of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS), vol. 54, pp. 1273-1282 (2017).
103. P. Kairouz, H.B. McMahan, B. Avent, A. Bellet, M. Bennis, A.N. Bhagoji, K. Bonawitz, Z. Charles, G. Cormode, R. Cummings, R.G.L. D'Oliveira, H. Eichner, S. El Rouayheb, D. Evans, J. Gardner, Z. Garrett, A. Gascón, B. Ghazi, P.B. Gibbons, M. Gruteser, Z. Harchaoui, C. He, L. He, Z. Huo, B. Hutchinson, J. Hsu, M. Jaggi, T. Javidi, G. Joshi, M. Khodak, J. Konečný, A. Korolova, F. Koushanfar, S. Koyejo, T. Lepoint, Y. Liu, P. Mittal, M. Mohri, R. Nock, A. Özgür, R. Pagh, H. Qi, D. Ramage, R. Raskar, M. Raykova, D. Song, W. Song, S. U. Stich, Z. Sun, A. T. Suresh, F. Tramèr, P. Vepakomma, J. Wang, L. Xiong, Z. Xu, Q. Yang, F.X. Yu, H. Yu and S. Zhao, *Found. Trends Mach. Learn.*, **14**, 1 (2021); https://doi.org/10.1561/2200000083