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Emerging contaminants threaten global water security and demand planetary-health-informed monitoring, treatment and governance solutions

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Systematic Review

Keywords: Emerging contaminants, Anthropocene, Planetary health, Water sustainability, Pharmaceuticals, Microplastics, Climate resilience

Posted Date: November 10th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11382338/v1

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Additional Declarations: No competing interests reported.

Abstract

Water systems in the Anthropocene are under unprecedented pressure from a diversifying array of emerging contaminants (EC), including pharmaceuticals, per- and polyfluoroalkyl substances (PFAS), microplastics, pesticides and endocrine-disrupting compounds, whose persistence, low-dose bioactivity and mixture effects challenge conventional water-quality paradigms. This review synthesizes literature published between 2020 and 2026 to examine the occurrence, transport and fate of EC and their ecological and human health implications through the lens of planetary health, a framework that explicitly links the stability of Earth's natural systems to human wellbeing. We also evaluate advances in screening analytics, sensor networks and machine-learning-enabled monitoring, alongside the emergence of Digital Twins as tools for predictive, adaptive water management. We further assess advanced treatment technologies, including advanced oxidation processes, membrane filtration and nanomaterial-based adsorbents within circular water management strategies that seek to recover water, energy and nutrients rather than treat wastewater as waste. This review situates the technical advances against the backdrop of planetary boundary transgression, climate-driven shifts in contaminant fate and the Sustainable Development Goals, particularly SDG 6 (clean water and sanitation) and SDG 3 (good health and wellbeing). We conclude by identifying critical research gaps, including the need for full-scale and low-resource-setting validation of AI-enabled monitoring, insufficient mixture-toxicity and transformation-product data, and the need for harmonized regulatory frameworks, and propose an integrated research agenda that couples analytical innovation, digital infrastructure and treatment engineering with planetary health governance.

1. Introduction

The Anthropocene, characterized by the pervasive imprint of human activity on Earth's biogeochemical cycles, has fundamentally altered the composition of the global hydrosphere. Water bodies were once considered pristine, but they now routinely contain complex mixtures of anthropogenic chemicals collectively termed emerging contaminants (EC): pharmaceuticals, personal care products, PFAS, microplastics, pesticides, and industrial compounds such as bisphenol A and flame retardants (Sauvé & Desrosiers, 2014; Li et al., 2024Compared to legacy pollutants regulated under long-standing frameworks many EC escape conventional wastewater treatment processes, persist across environmental compartments and exert biological effects at trace concentrations, sometimes in the range of nanograms per liter (Petrie et al., 2015; Richardson & Ternes, 2018). The planetary health framework was formalized by the Rockefeller Foundation–Lancet Commission on Planetary Health, reframing environmental degradation as not just an ecological concern but a direct threat to human health. It argues that civilization has been mortgaging the health of future generations to sustain present-day economic gains (Whitmee et al., 2015). Water sustainability sits at the centre of this framework, as roughly four billion people already experience severe water scarcity during at least one month of the year (Mekonnen & Hoekstra, 2016), and threats to human water security are widespread (Vörösmarty et al., 2010). The planetary boundaries framework operationalizes these risks quantitatively, and the Planetary Health Check 2025 reports that seven of the nine boundaries have now been

transgressed, among them freshwater change, novel entities and, for the first time, ocean acidification (Sakschewski et al., 2025; Richardson et al., 2023; Steffen et al., 2015). PFAS in particular have been proposed as justification for a dedicated planetary boundary given their extreme persistence and ubiquitous distribution (Cousins et al., 2022; Persson et al., 2022).

Against this backdrop, water sustainability requires simultaneous transformation on three fronts: (i) understanding the occurrence, transport, and toxicological impact of EC; (ii) deploying the next-generation monitoring and predictive technologies, including artificial intelligence (AI), machine learning (ML), and Digital Twins; and (iii) transitioning from linear, end of pipe treatment toward circular water management that recovers resources while removing contaminants. This review synthesizes literature from 2020 to 2026 across these three fronts, explicitly connecting technical and scientific advances to the planetary health framework and the United Nations Sustainable Development Goals (SDG), particularly SDG 6 on clean water and sanitation. Several existing reviews address individual strands of this landscape in depth, for example PFAS occurrence and treatment, microplastics ecotoxicology, or Digital Twin architectures in isolation, and some integrate monitoring, treatment and governance, but to our knowledge few explicitly connect EC occurrence, AI/ML and Digital Twin monitoring, treatment engineering and planetary health governance within a single synthesis. This review's contribution is that connection: it situates recent (2020–2026) technical advances in analytics and treatment against the planetary boundaries and SDG framing, so that monitoring, treatment, and governance are read as interdependent components of one water security problem rather than as separate literatures. Integrated monitoring frameworks for planetary health have been proposed (Haines et al., 2019); this review asks how monitoring of emerging contaminants in water could connect to them.

2. Review Methodology

Literature underpinning this review was identified through searches of Google Scholar, Elsevier (ScienceDirect), and SpringerLink, conducted between January 10, 2026 and July 30, 2026, using the following search terms combined with the Boolean operators AND/OR (Google Scholar does not support field-restricted syntax such as Scopus TITLE-ABS-KEY, so terms were combined as free-text/phrase search on that platform; ScienceDirect and SpringerLink support field-restricted search and were queried accordingly where their interfaces allowed): ("emerging contaminants" OR PFAS OR "per- and polyfluoroalkyl substances" OR microplastics OR pharmaceuticals OR "endocrine disrupting compounds") AND (water OR wastewater OR groundwater) AND ("planetary health" OR "digital twin" OR "machine learning" OR "artificial intelligence" OR treatment), restricted where possible to peer-reviewed journal articles and reviews published in English. Candidate records from all three sources were exported into Mendeley reference management software, where they were de-duplicated and screened against explicit eligibility criteria: sources were retained if they were peer-reviewed journal articles or reviews published in a Scopus-indexed journal, published in English, and topically relevant to emerging contaminant occurrence, monitoring and predictive technologies, treatment approaches, or planetary health framing; sources were excluded if they did not concern water, wastewater, or groundwater matrices, if they addressed only legacy/regulated pollutants without reference to emerging

contaminants, or if the publishing journal was not indexed in Scopus. Scopus was not a fourth search platform in its own right but a post-hoc quality filter for candidate records retrieved from Google Scholar, ScienceDirect and SpringerLink; journal indexing status was checked against the Scopus source list at the time of screening. Screening of titles/abstracts and eligibility judgments were performed by a single author (Dhanraj M R; see Author Contributions). A combined search across Google Scholar, ScienceDirect and SpringerLink retrieved 110 records which were imported into Mendeley, de-duplicated and screened against the eligibility criteria; 72 were retained for synthesis. The entire text of each selected source was read and summarized to extract key findings, and these were collated and synthesized in this narrative review. Citations were inserted and the reference list compiled using the citation and bibliography tools of Microsoft Word. The search was limited to recent publications (mostly from 2020–2026) to define current research trends and to give a future perspective on the field. The reference list also contains a handful of earlier seminal references on planetary boundaries and micropollutant frameworks (e.g., Rockström et al., 2009; Schwarzenbach et al., 2006) that are conceptually central to the framing of the review but outside the 2020–2026 window; these were identified through citation tracking rather than the three database searches themselves; the authors added these references to the reference list using Microsoft Word. The main policy source cited is the regulation by USEPA(2024), not a journal article. During revision one further source (Sakschewski et al., 2025) was added to update the planetary boundary status, thus the reference list contains 73 entries. The current review is narrative, not systematic (i.e. PRISMA-registered), with no formal protocol pre-registered and no inclusion beyond the above criteria other than author judgment of topical relevance and recency, rather than a fixed, independently reproducible eligibility algorithm applied to a bounded search return. Otherwise, the report is based on the general recommendations of the Scale for the Assessment of Narrative Review Articles (SANRA; Baethge et al., 2019) for the justification of the importance of the review, description of the literature search, and transparent reasoning about evidence.

2.1 Limitations of the Review Methodology

This review is subject to several methodological limitations that should be considered when interpreting its conclusions. First, literature was identified through three sources: Google Scholar, Elsevier (ScienceDirect), and SpringerLink, rather than a comprehensive bibliographic database such as Scopus or Web of Science; no cross-validation against those databases or grey literature sources was performed. This is a meaningful limitation even with three sources, principally because of Google Scholar: its index, ranking algorithm, and result set are not fully transparent or independently reproducible, and results can vary by access date, location, and account personalization, and it does not support the field-restricted, auditable Boolean queries (e.g., title/abstract/keyword restricted search) that ScienceDirect, SpringerLink, and databases such as Scopus provide. In addition, ScienceDirect and SpringerLink each index only their respective publishers' journals, so together with Google Scholar they still do not offer the cross-publisher coverage of a database such as Scopus or Web of Science, and articles published outside Elsevier and Springer venues were only reachable through the Google Scholar arm of the search. Candidate records from all three sources were, however, exported into Mendeley

reference management software and de-duplicated there, which provides a partial audit trail for the screening process even though the initial searches are not exactly reproducible by a third party. Requiring retained sources to be published in a Scopus-indexed journal (see Section 2) partially mitigates the transparency concerns raised above, since it applies an independently verifiable quality threshold to the 72 retained sources regardless of which of the three platforms first surfaced them; it does not, however, resolve the underlying reproducibility limitation of the initial retrieval step itself, and it may additionally exclude relevant non-Scopus-indexed journals, particularly regional or non-English language venues. This may introduce coverage bias, particularly for non-English or regionally indexed literature relevant to low- and middle-income settings. Second, search, screening, and eligibility judgments were performed by a single author (Dhanraj M R), with review and editing by co-authors after drafting; single-screener selection is a recognized limitation for narrative reviews relative to dual-reviewer or consensus-based screening, and raises the possibility of selection bias that a second, independent screener would help detect. Third, the English language restriction and reliance on peer-reviewed, published (predominantly statistically significant or "successful") findings likely underrepresent negative or null results, non-English literature, and grey literature. Finally, the review focuses on recent (2020–2026) literature to capture current trends and selectively represents the slower moving or foundational work outside this window by citation tracking rather than exhaustively. These limitations are consistent with the narrative rather than systematic nature of the review and are reported here for methodological transparency reasons. They should be interpreted alongside the synthesis in Sections 3–9.

3. Emerging Contaminants: Classification, Sources, and Global Occurrence

3.1 Pharmaceuticals and Personal Care Products

Pharmaceuticals are still among the most reported EC in freshwater systems worldwide. A bibliometric analysis of the literature between 2001 and 2021 shows a steady increase in research hotspots about antibiotics, analgesics and psychiatric drugs (Yu et al., 2024). Occurrence surveys have reported wide ranges of concentrations depending on geographic region and analyte. The quantification of sulfonamide and fluoroquinolone antibiotics in groundwater across Europe, East Africa and Asia has been reported in the range of tens to hundreds of nanograms per liter. Common analgesics including acetaminophen and NSAIDs are often found at higher concentrations illustrating their extensive use (Li et al., 2020). A large-scale monitoring study across 258 rivers on six continents found pharmaceutical contamination to be a global phenomenon affecting waterways regardless of national income level (Wilkinson et al., 2022), while composite sampling of wastewater treatment plant influents and effluents confirms that caffeine, analgesics, and select antibiotics are detected with near-universal frequency, demonstrating the limited efficacy of conventional secondary treatment for many polar, non-biodegradable pharmaceutical residues.

Pharmaceuticals enter aquatic systems via human excretion, incorrect disposal, hospital wastewater, veterinary use and the application of biosolids as agricultural fertilizer. The latter route introduces pharmaceuticals directly into the soil-crop system and has been shown to result in measurable plant uptake in irrigated agriculture (Prosser & Sibley, 2015). The second, parallel and more urgent issue is the environmental selection and horizontal transfer of antibiotic resistance genes (ARG) in bacterial communities exposed to sub-inhibitory concentrations of antibiotics, a process directly relevant to global public health with the rise of multi-drug resistant pathogens (Lin et al., 2021; Liu et al., 2022). In addition, the transformation products formed in treatment or environmental degradation may retain or even exceed the ecotoxicological potency of parent antimicrobial compounds, making risk assessment more complex (Löffler et al., 2023).

Values reported in different water matrices (groundwater, surface water and wastewater treatment plant influent), regions and analytical methods are presented in Table 1 *and are provided here to show the range of concentrations reported in the literature rather than being directly comparable. Cross matrix or cross region comparisons should consider these methodological differences.*

Table 1
Reported concentrations of selected pharmaceutical compounds in global surface water, groundwater, and wastewater matrices (2019–2025).

Compound class	Representative compound	Matrix / region	Reported concentration	References
Antibiotic (sulfonamide)	Sulfadiazine	Groundwater, Spain	208 ng/L	Jurado et al. (2020), cited in Wada & Olawade (2025)
Antibiotic (sulfonamide)	Sulfamethoxazole	Groundwater, Kenya	258.2 ng/L	Karimi et al. (2023), cited in Wada & Olawade (2025)
Antibiotic (sulfonamide)	Sulfamethoxazole	Groundwater, Cameroon	73 ng/L	Branchet et al. (2019), cited in Wada & Olawade (2025)
Antibiotic (sulfonamide)	Sulfamethoxazole	Groundwater, Tanzania	94 ng/L	Kundu et al. (2024), cited in Wada & Olawade (2025)
Antibiotic (fluoroquinolone)	Fleroxacin	Surface water, China	26.6 ng/L	Gu et al. (2019), cited in Wada & Olawade (2025)
Analgesic / NSAID	Acetaminophen	Groundwater, Pennsylvania, USA	122.7 ng/L	Kibuye et al. (2019), cited in Wada & Olawade (2025)
Analgesic / NSAID	Mefenamic acid	River water, Canada	1,848 ng/L	Husk et al. (2019), cited in Wada & Olawade (2025)
Analgesic / NSAID	2-Hydroxyibuprofen (transformation product)	WWTP influent, multi-country	up to 5,623 ng/L	Paíga et al. (2025)
Stimulant	Caffeine	WWTP influent, multi-country (97-compound survey)	up to 12,664 ng/L	Paíga et al. (2025)

3.2 Per- and Polyfluoroalkyl Substances (PFAS)

PFAS are a group of thousands of synthetic compounds that have a very strong carbon–fluorine bond that does not break down in the environment, hence the name “forever chemicals” (Wackett, 2024). Long range transport has been seen even to remote glacial environments, showing the near-global distribution of these compounds, regardless of proximity to point sources (Kwok et al., 2013). Regulatory momentum has been building. The U.S. Environmental Protection Agency finalized its first National Primary Drinking Water Regulation for six PFAS compounds in April 2024 (USEPA, 2024) and the revised European Union Drinking Water Directive has included monitoring obligations for structurally analogous emerging pollutants. As of this writing, portions of the 2024 U.S. rule remain in regulatory flux: in 2025, the EPA proposed to extend compliance deadlines and re-evaluate standards for several of the six regulated PFAS, so readers should check the current status of individual maximum contaminant levels against the EPA PFAS drinking water webpage before quoting figures from this review as current policy.

Adsorption-based approaches in water treatment still face technical and economic challenges. Granular activated carbon and anion exchange resins are the most mature technologies but generate waste streams laden with PFAS that require further management (Rahman et al., 2014; Appleman et al., 2014; Zaggia et al., 2016; Tushar et al., 2024). Destructive technologies, such as advanced reduction and electrochemical oxidation, have attracted increasing attention because they can mineralize the carbon–fluorine bond instead of just concentrating it, but most are still at laboratory or pilot scale (Ateia et al., 2019). Machine-learning-assisted non-target screening is increasingly being applied to trace PFAS source fingerprints in impacted watersheds, providing a route to more targeted source control (Joseph et al., 2023). Given their persistence, bioaccumulation and evidence of adverse reproductive, immunological and metabolic health effects, several authors have argued that PFAS alone justify recognition as having breached a dedicated planetary boundary for persistent, mobile and toxic substances (Cousins et al., 2022).

3.3 Microplastics

Microplastics are defined as synthetic polymer particles smaller than 5 mm, and in the last decade, they have changed from mainly a marine research topic to a topic of intensive research in freshwater environments (Wang et al., 2023). Sources include fragmentation of larger plastic debris, synthetic textile fibers, additives from personal care products and tyre wear.

Fibres are often the dominant morphology in freshwater systems. When ingested, microplastics can lead to physical damage of gut tissue, and serve as vectors for co-contaminants such as heavy metals and hydrophobic organic pollutants that adhere to their surfaces, thereby increasing the toxicological risk beyond that of the polymer itself (Ma et al., 2020). Toxicity is highly dependent on size and shape, with fibrous particles generally more harmful than spherical microbeads of similar polymer composition. Standardization of analytical methods remains a challenge because of heterogeneous sampling protocols; polymer identification methods and size-class definitions also differ across studies, which complicates cross-study comparison and global synthesis. The lack of a harmonized minimum reporting standard, like the concentration-range caveat noted for Table 1, means that reported freshwater microplastic abundances (commonly spanning several orders of magnitude, from below 1 to several

thousand particles per litre or per kilogram of sediment depending on matrix and size cutoff) are difficult to compare directly across the literature, and likely explains part of the wide variability reported between studies of superficially similar water bodies. Regulatory measures such as the European Union (EU) ban on intentionally added microplastics in cosmetic products are an early but partial response that does not target the dominant secondary sources of fragmentation and fiber shedding (Kentin & Kaarto, 2018). Since the majority of environmental microplastic loading is derived from secondary fragmentation of larger plastic items and fiber release during laundering rather than from intentionally added particles, product-level bans such as the one adopted by the EU are necessarily a partial response and upstream measures at the level of textile and packaging design have been proposed as a complementary, albeit less mature, regulatory avenue.

3.4 Pesticides and Endocrine Disrupting Compounds

Pesticides are extensively used in agriculture and recent epidemiological evidence has associated exposure to pesticides with adverse health outcomes, including cancer (Cavalier et al., 2023). Several mechanisms are expected to intensify this trend in the face of climate change: increasing temperatures and changing precipitation patterns extend pest ranges and growing seasons, leading to more frequent and intensive pesticide application, while changes in rainfall intensity increase the likelihood of storm-induced runoff and flooding events that transport soil-bound residues into surface waters (Yang et al., 2024; Brüggemann et al., 2024). Climate change may also change the toxicity of pesticides to non-target organisms such as earthworms (Kaka et al., 2021). Long-term monitoring datasets reveal that some herbicides and their transformation products are commonly detected in agricultural watersheds across multi-decadal timescales (Chow et al., 2020).

Endocrine disrupting compounds (EDCs) such as bisphenol A, certain pesticides and flame retardants interfere with hormonal signaling in humans and wildlife. This results in reproductive, developmental and metabolic effects even at low, environmentally relevant concentrations. Effects are often non-monotonic, meaning that low-dose exposure can elicit a disproportionately greater biological response than intermediate doses, making it difficult to apply the conventional high-to-low-dose extrapolation typical of regulatory toxicology and an ongoing point of contention between EDC researchers and traditional risk-assessment frameworks. Mixture toxicity, rather than single-compound risk, is increasingly recognized as the more ecologically and toxicologically relevant exposure scenario because EDCs, pharmaceuticals and PFAS are often found together in the same water bodies, however, standardized frameworks for assessing combined effects are still underdeveloped (Kroon et al., 2020). Therefore, agricultural intensification and EDC occurrence are connected results of the same land use pressures detailed for pesticides above, which bolsters the argument for regulating these compound classes as a linked exposure system, not in separate chemical silos.

4. Environmental Transport, Fate, and Ecological and Human Health Impacts

EC enter aquatic systems through point sources (wastewater treatment plant effluent, industrial discharge) and diffuse sources (agricultural runoff, atmospheric deposition, urban stormwater). Subsequently, the fate of EC is governed by physicochemical properties including polarity, volatility, sorption affinity and susceptibility to biotic and abiotic environmental transformation. Surface water–groundwater exchange results in cross-migration of pollutants which may jeopardize drinking water aquifers (Li et al., 2024). Climate change is directly impacting transport system dynamics, including flooding frequency, and experimental evidence indicates that pesticide deposition in riparian soils and vegetation increases with climate change. Changes in hydrological regimes alter dilution capacity and residence time in receiving waters, with cascading implications for peak contaminant concentrations during low-flow and high-temperature periods.

Ecotoxicological effects are observed on different levels of biological organization, ranging from the subcellular level with endocrine disruption to population-level effects on reproduction, growth and behaviour in fish, amphibians and invertebrates. Antimicrobial and antibiotic resistance pollution also endangers human health indirectly, by enabling the evolution and environmental persistence of resistant bacterial strains capable of horizontal gene transfer to human pathogens (Lin et al., 2021). From a planetary health perspective, these impacts cannot be considered in isolation, as freshwater ecosystem degradation reduces the regulating and provisioning services on which human food security, disease control and psychological wellbeing depend, illustrating the intimate coupling between ecological integrity and human health emphasized throughout the planetary health literature (Whitmee et al., 2015; Tong & Bambrick, 2022).

5. Analytical Advances in Monitoring Emerging Contaminants

High resolution mass spectrometry (HRMS) coupled with liquid or gas chromatography has become the analytical backbone of modern EC monitoring enabling targeted quantification and suspect and non-target screening (NTS) for compounds that do not have a reference standard (Guo et al., 2020; Tadić et al., 2022). NTS workflows are of particular value because raw HRMS data can be queried retrospectively as new contaminants of concern are identified without the need for repeat sampling campaigns. However, matrix effects, retention time drift, and incomplete spectral libraries still plague NTS, as does the inability of high mass resolution to distinguish structural isomers (Rebryk & Haglund, 2020).

Artificial intelligence is used more and more in NTS workflows to accelerate compound identification, identify candidate features for confirmation, and link contaminant fingerprints to likely pollution sources. Recent applications include ML-assisted suspect screening to track PFAS source signatures and to identify chemical markers of groundwater contamination pathways (Joseph et al., 2023; Ekpe et al., 2024). They are useful because they reduce the huge candidate space generated by HRMS to a manageable shortlist for confirmation, not because they replace expert spectral interpretation, and that is what the ML-assisted workflows do. The practical bottleneck reported across studies is less the algorithms themselves, but rather the lack of curated, matrix-matched reference spectra for training and validating them. This helps to understand why NTS-ML applications are still limited to a few well-studied

compound classes (PFAS, pharmaceuticals) and not to the whole scope of EC. Monitoring capability is being expanded beyond centralized labs by complementary advances in biosensors, passive samplers, and portable field-deployable instruments. There is a critical need to fill surveillance gaps in low-resource settings, which are routinely underrepresented in the global EC literature.

6. Artificial Intelligence, Machine Learning, and Digital Twins in Water Quality Management

6.1 AI and Machine Learning for Water Quality Assessment

AI and ML methods, from artificial neural networks (ANNs) and support vector machines to deep learning architectures, are used throughout the water quality management pipeline for predicting water quality indices, detecting contaminants, reducing the dimensionality of complex monitoring datasets, detecting anomalies in real-time monitoring systems, and forecasting contaminant loading under variable hydrological conditions (Frincu, 2025; Essamlali et al., 2024). Long short-term memory (LSTM) networks have demonstrated a strong performance over decades of water quality time series, while hybrid physics-informed and data-driven models are increasingly favoured over purely empirical approaches because they retain interpretability and generalize better to unseen conditions (Su et al., 2024; Nearing et al., 2021). Generative AI is also emerging as a tool for water utility operations, providing capabilities to generate scenarios, synthesize reports and support operator decisions (Sela et al., 2025). Yet, despite this progress, several barriers still hinder real-world deployment: computational scalability, lack of standardized evaluation metrics across studies, limited explainability of deep learning outputs, and minimal validation in low-resource or data-scarce settings where monitoring infrastructure is weakest (Frincu, 2025; Olawade et al., 2024). Deep learning applications in urban water management, while promising for early warning systems and pollutant source tracking, similarly face challenges around training data availability and model transferability across geographically and hydrologically distinct catchments (Fu et al., 2022). The R^2 values in Table 2 (0.97 and 0.992), from Makumbura et al. (2024) and Nishat et al. (2025), come from two studies that used different datasets, water quality index formulations and validation schemes, so they show the performance each study reported and do not rank the models, and high in-sample fit does not necessarily indicate that the same architecture would generalize to a hydrologically distinct catchment. Tree ensembles, neural networks and LSTM models have been applied to water quality index prediction in many other settings (Walczak & Walczak, 2025; Han et al., 2025; Zhang et al., 2025). Machine learning has also been used to weight toxicity-based prioritization of monitoring compounds (Ekpe et al., 2025), which is a different task from index prediction and is therefore not compared in Table 2.

Table 2
Reported performance of two machine-learning studies that predict a water quality index (values as given in each study's abstract). The studies use different datasets, index formulations and validation schemes, so the values illustrate reported performance and do not rank the models.

Model	Study context	R^2	RMSE / MAE (as reported)	Reference
Random Forest, LightGBM and XGBoost compared	Weighted arithmetic water quality index, regression with SHAP interpretation	0.992	RMSE = 1.381; MAE = 0.825	Makumbura et al. (2024)
Artificial neural network (best of 14 models)	Dhaka rivers, Bangladesh; water quality index regression	0.97	RMSE = 2.34; MAE = 1.24; NSE = 0.97	Nishat et al. (2025)

6.2 Digital Twins for Water Infrastructure

Digital Twins (DT), dynamic virtual replicas of physical water and wastewater systems maintained through continuous bidirectional data exchange, are a rapidly maturing application of AI in the water sector. A recent review of DT applications in the water sector reports growing research activity, focused primarily on water distribution networks, wastewater treatment and drinking water treatment (Ghorbani Bam et al., 2025). The effect of digital transformation on carbon emissions in the water industry has also been examined (Beji & Lade, 2022). In full-scale implementations such as the Changi Water Reclamation Plant in Singapore, the Eindhoven Water Resource Recovery Facility in the Netherlands and the Cuxhaven treatment plant in Germany, tangible operational benefits have been reported including forecasting of process events several days in advance and reductions in aeration energy demand through ML-assisted nutrient-load estimation. The magnitude of savings varies a lot between studies and from full-scale site to full-scale site, and it is not yet standardized for direct comparison between facilities (Wang et al., 2024; Ghorbani Bam et al., 2025).

However, the literature suggests that the vast majority of full-scale DT only operate in advisory mode, with automated bidirectional control being rare due to regulatory liability, cybersecurity concerns, and the practical difficulty of encoding the full set of physical and safety constraints embedded in proprietary SCADA and programmable logic controller systems (Homaei et al., 2024). Hybrid soft-sensor approaches that combine mechanistic process models with machine-learned residual correction are emerging as a practical middle ground, improving predictive fidelity while preserving interpretability for regulatory trust (Wang et al., 2024). DT research and deployment are geographically concentrated in high-income countries, raising equity concerns consistent with the broader environmental justice dimension of planetary health, as utilities in low- and middle-income regions, often those facing the most acute water security challenges, remain largely absent from the current evidence base (Ghorbani Bam et al., 2025).

7. Advanced Treatment Technologies and Circular Water Management

Advanced oxidation processes (AOPs) produce highly reactive hydroxyl and sulfate radicals that can mineralize recalcitrant organic pollutants and have been shown to remove various EC, including pharmaceuticals, dyes and industrial chemicals, in laboratory and pilot studies, as well as improving effluent biodegradability and reducing sludge production compared with conventional biological treatment. Specifically, ozonation combined with activated carbon adsorption has proven to be effective against regulated and candidate EC in drinking water settings, although at higher capital and operating costs than conventional treatment trains (Cantoni et al., 2024). Active areas of innovation include emerging catalyst structures, membrane-integrated AOP and renewable-energy-coupled reactor designs that are targeted at reducing the substantial energy intensity that currently limits full-scale AOP adoption, particularly in resource-constrained settings. Treatment technologies for emerging contaminants in wastewater treatment plants have been reviewed extensively (Rout et al., 2021).

Table 3
Qualitative comparison of treatment options for PFAS. Numerical removal is given only for ball-milled colloidal activated carbon, from one laboratory batch study; the sources for the other technologies address cost, sustainability or brine treatment rather than removal efficiency.

Technology	Reported removal (numbers only where verified)	Chain-length considerations (qualitative)	Relative cost and sustainability (qualitative)	Reference
Granular activated carbon (GAC)	Not quantified in this review	Lower and variable for short-chain PFAS	Costlier than ion exchange for long-chain PFAS because of rapid breakthrough and carbon replacement	Tushar et al. (2024)
Anion-exchange resin (IX)	Not quantified in this review	More effective for long-chain PFAS; chain-length dependent	Cost-effective and environmentally favourable for long-chain PFAS in the cases reviewed	Tushar et al. (2024)
Reverse osmosis / nanofiltration	Not quantified in this review	Not assessed	Produces a PFAS-enriched brine that needs further treatment	Xie et al. (2025)
Ball-milled colloidal activated carbon	PFOS 89%, PFOA 73%, PFBS 55%, PFBA 30% (maximum values, laboratory batch study)	Removal falls with decreasing chain length	Emerging; laboratory scale only	Mahlet M. Kebede et al. (2025)

Circular water management treats wastewater treatment as a platform for resource recovery: recovering water for reuse, energy through anaerobic digestion and biogas capture, and nutrients such as nitrogen and phosphorus for agricultural application, instead of treating wastewater as waste to be disposed of. Integrative sustainability assessments of membrane filtration and anaerobic digestion, combining life

cycle assessment, carbon footprint analysis and techno-economic evaluation, increasingly inform technology selection, identifying pathways to simultaneously minimize greenhouse gas emissions and maximize water reuse potential. Adsorption remains cost competitive with AOP in many settings, and hybrid adsorption–AOP treatment trains are gaining momentum under revised urban wastewater treatment directives that increasingly mandate quaternary treatment for contaminants of emerging concern.

In the case of PFAS, sustainability assessments emphasize the ongoing tradeoffs between treatment efficacy and environmental footprint for adsorption technologies capable of effectively removing PFAS, but generating concentrated waste streams that require additional destruction or disposal, and destructive technologies capable of breaking the carbon-fluorine bond, but being energy intensive and largely unproven at full scale (Tushar et al., 2024). Training in integrated capture and on-site destruction treatment is increasingly being proposed as a way to eliminate secondary waste streams, indicating a wider move away from linear to closed-loop contaminant management in circular water systems.

8. Climate Resilience and the Planetary Health Sustainable Development Goals Nexus

Water sustainability, emerging contaminant management and planetary health are structurally interdependent within the framework of sustainable development goals. However, progress toward SDG 6, in turn, supports SDG 3 (good health and wellbeing), SDG 14 (life below water) and SDG 15 (life on land) (Frincu, 2025). The degradation of freshwater ecosystems driven by EC remains largely unchecked, and SDG 6 (clean water and sanitation) cannot be achieved. The planetary health framework provides a conceptual scaffolding to render these interdependencies explicit, framing freshwater integrity not as a sectoral environmental issue, but as a fundamental determinant of human civilizational stability (Rockström, 2025; Tong & Bambrick, 2022).

Climate change is a threat multiplier across this nexus. In addition to its direct effect on contaminant transport and fate discussed in Section 4, climate change is expected to increase water scarcity, increase the frequency of both drought and extreme precipitation events, and increase the energy and financial cost of maintaining resilient water treatment infrastructure (Boretti & Rosa, 2019; Mekonnen & Hoekstra, 2016). Recent earth system science reports indicate that seven of nine planetary boundaries have been transgressed (Sakschewski et al., 2025), including freshwater change and novel entities, a category that explicitly includes PFAS, microplastics and other persistent synthetic chemicals (Steffen et al., 2015; Richardson et al., 2023; Persson et al., 2022). This evidence strengthens calls, heard throughout the planetary health literature, for governance approaches to chemical pollution, biodiversity loss and climate change as a single, interconnected crisis, not as separate policy silos (Rockström et al., 2009; Naidu et al., 2021).

9. Critical Research Gaps and Future Directions

Mixture toxicity and transformation products are still largely under characterized: most regulatory and monitoring frameworks are compound specific, but real-world exposure involves complex, co-occurring mixtures of parent compounds and their transformation products, whose combined toxicological significance is not yet well understood (Löffler et al., 2023; Kroon et al., 2020). There remain persistent gaps in the equity of monitoring and digital infrastructure: AI-enabled monitoring and Digital Twin deployment are still concentrated in high-income countries and full-scale utilities and validated low-cost approaches for low- and middle-income regions and decentralized systems are urgently needed (Ghorbani Bam et al., 2025; Olawade et al., 2024). There is also limited full-scale validation of destructive PFAS and AOP technologies; lab-scale successes have not consistently translated to full-scale, real-matrix performance, and techno-economic and life cycle data at scale remain sparse (Tushar et al., 2024; Ateia et al., 2019). Standardization of microplastics analytics is also needed, as heterogeneous sampling and quantification protocols hinder cross-study synthesis and global risk assessment (Wang et al., 2023). Climate–contaminant interaction modeling is still in its infancy: coupled climate–fate–transport models predicting pesticide, pharmaceutical and PFAS risk in combination in future climate scenarios are not yet mature (Yang et al., 2024; Brüggemann et al., 2024). Explainability and trust in AI-driven water management need to be further enhanced. Regulatory and operator trust in ML-based decision support depends on further progress on model interpretability, uncertainty quantification, and transparent encoding of constraints for closed-loop control (Homaei et al., 2024; Frincu, 2025). Finally, integrated planetary health governance is weak. Fragmented sectoral regulation of water, chemicals and climate policy is poorly aligned with the systemic, cross-boundary nature of planetary health risks, calling for governance innovation alongside technical innovation (Rockström, 2025; Whitmee et al., 2015).

10. Conclusion

The convergence of emerging contaminant pollution, accelerating climate change, and planetary boundary transgression positions water sustainability as one of the defining challenges of the Anthropocene. This review has shown that meaningful progress requires advances on three mutually reinforcing fronts: deepening scientific understanding of EC occurrence, transport, and mixture toxicity; deploying AI, machine learning, and Digital Twin technologies to enable predictive, adaptive water management and transitioning treatment infrastructure toward circular, resource-recovering models rather than linear, end-of-pipe disposal. Realizing these advances at the pace and scale the crisis demands will require not only continued technical innovation but also governance frameworks explicitly grounded in the planetary health paradigm, frameworks capable of treating water, chemical pollution, and climate resilience as an integrated system rather than as isolated policy domains. Only through such integration can water sustainability be secured for both present and future generations.

Declarations

Declaration of generative AI and AI-assisted technologies in the writing process

This manuscript was manually drafted and no AI was used.

Funding

This research received no external funding.

Author contribution

The first author, Dhanraj M R, participated in compilation of the literature, drafting the manuscript, search and synthesis, and data extraction. Second author Nausha Shetty helped with review and editing and structuring the document. The third author, Manasmitha R Shettigar helped with visualization, editing and data from pharmaceutical journals. Mithesh Kumar contributed to review and structuring of the document. Arjun Shetty, the fifth author, assisted with the preparation of the reference list. Sixth author Seema S helped with formatting and grammar correction.

Declaration of competing interest

The authors have no competing interests.

Ethics Approval

Not applicable

Consent to participate

Not applicable

Data availability

Not applicable

Consent to Publish

Not applicable

Clinical Trial Number

Not applicable

References

1. Appleman TD, Higgins CP, Quiñones O, Vanderford BJ, Kolstad C, Zeigler-Holady JC, Dickenson ERV. Treatment of poly- and perfluoroalkyl substances in U.S. full-scale water treatment systems. Water Res. 2014;51:246–55.
2. Ateia M, Maroli A, Tharayil N, Karanfil T. The overlooked short- and ultrashort-chain poly- and perfluorinated substances: A review. Chemosphere. 2019;220:866–82.

3. Baethge C, Goldbeck-Wood S, Mertens S. SANRA—a scale for the quality assessment of narrative review articles. Res Integr Peer Rev. 2019;4:5.
4. Beji H, Lade M. Impact of digital transformation on carbon emissions reductions in the water industry. Lecture Notes in Energy. Springer International Publishing; 2022.
5. Boretti A, Rosa L. (2019). Reassessing the projections of the World Water Development Report. npj Clean Water, 2, 15.
6. Brüggemann M, et al. Measuring pesticides in the atmosphere: Current status, emerging trends and future perspectives. Environ Sci Europe. 2024;36:39.
7. Cantoni B, Ianes J, Bertolo B, Ziccardi S, Maffini F, Antonelli M. Adsorption on activated carbon combined with ozonation for the removal of contaminants of emerging concern in drinking water. J Environ Manage. 2024;350:119537.
8. Cavalier H, Trasande L, Porta M. Exposures to pesticides and risk of cancer: Evaluation of recent epidemiological evidence in humans and paths forward. Int J Cancer. 2023;152:879–912.
9. Chow R, et al. A review of long-term pesticide monitoring studies to assess surface water quality trends. Water Res X. 2020;9:100064.
10. Cousins IT, Johansson JH, Salter ME, Sha B, Scheringer M. Outside the safe operating space of a new planetary boundary for per- and polyfluoroalkyl substances (PFAS). Environ Sci Technol. 2022;56(16):11172–9.
11. Ekpe OD, Choo G, Kang J-K, Yun S-T, Oh J-E. Identification of organic chemical indicators for tracking pollution sources in groundwater by machine learning from GC-HRMS-based suspect and non-target screening data. Water Res. 2024;252:121130.
12. Ekpe OD, Moon H, Pyo J, Oh J-E. Prioritization of monitoring compounds from SNTS identified organic micropollutants in contaminated groundwater using a machine learning optimized ToxPi model. Water Res. 2025;270:122824.
13. Essamlali I, Nhaila H, Khaili E, M. Advances in machine learning and IoT for water quality monitoring: A comprehensive review. Heliyon. 2024;10:e27920.
14. Frincu RM. Artificial intelligence in water quality monitoring: A review of water quality assessment applications. Water Qual Res J. 2025;60(1):164–76.
15. Fu G, Jin Y, Sun S, Yuan Z, Butler D. The role of deep learning in urban water management: A critical review. Water Res. 2022;223:119098.
16. Ghorbani Bam P, Rezaei N, Roubanis A, Austin D, Austin E, Tarroja B, Takács I, Villez K, Rosso D. Digital twin applications in the water sector: A review. Water. 2025;17(20):2957.
17. Guo Z, Huang S, Wang J, Feng Y-L. Recent advances in non-targeted screening analysis using liquid chromatography–high resolution mass spectrometry to explore new biomarkers for human exposure. Talanta. 2020;219:121339.
18. Haines A, Hanson C, Ranganathan J. Planetary Health Watch: Integrated monitoring in the Anthropocene epoch. Lancet Planet Health. 2019;3(2):e65–7.

19. Han Z, Zhang S, He L. Predicting and investigating water quality index by robust machine learning methods. J Environ Manage. 2025;381:125156.
20. Homaei M, Mogollón-Gutiérrez Ó, Sancho JC, Ávila M, Caro A. A review of digital twins and their application in cybersecurity based on artificial intelligence. Artif Intell Rev. 2024;57(8):201.
21. Joseph NT, et al. Target and suspect screening integrated with machine learning to discover per- and polyfluoroalkyl substance source fingerprints. Environ Sci Technol. 2023;57:14351–62.
22. Kaka H, Opute PA, Maboeta MS. (2021). Potential impacts of climate change on the toxicity of pesticides towards earthworms. Scientific World Journal, 2021, 8527991.
23. Kentin E, Kaarto H. An EU ban on microplastics in cosmetic products and the right to regulate. Rev Eur Comp Int Environ Law. 2018;27(3):254–66.
24. Kroon FJ, Berry KLE, Brinkman DL, et al. Sources, presence and potential effects of contaminants of emerging concern in the marine environments of the Great Barrier Reef and Torres Strait, Australia. Sci Total Environ. 2020;719:135140.
25. Kwok KY, et al. Transport of perfluoroalkyl substances (PFAS) from an Arctic glacier to downstream locations: Implications for sources. Sci Total Environ. 2013;447:46–55.
26. Li W, Ma Z, Li J, Li Q, Li Y, Yang J. (2024). Digital twin smart water conservancy: Status, challenges, and prospects. Water, 16(14), 2038.
27. Li X, Shen X, Jiang W, Xi Y, Li S. Comprehensive review of emerging contaminants: Detection technologies, environmental impact, and management strategies. Ecotoxicol Environ Saf. 2024;278:116420.
28. Li Y, Zhang L, Ding J, Liu X. Prioritization of pharmaceuticals in water environment in China based on environmental criteria and risk analysis of top-priority pharmaceuticals. J Environ Manage. 2020;253:109732.
29. Lin Z, Yuan T, Zhou L, Cheng S, Qu X, Lu P, Feng Q. Impact factors of the accumulation, migration and spread of antibiotic resistance in the environment. Environ Geochem Health. 2021;43(5):1741–58.
30. Liu G, Thomsen LE, Olsen JE. Antimicrobial-induced horizontal transfer of antimicrobial resistance genes in bacteria: A mini-review. J Antimicrob Chemother. 2022;77(3):556–67.
31. Löffler P, Escher BI, Baduel C, Virta MP, Lai FY. Antimicrobial transformation products in the aquatic environment: Global occurrence, ecotoxicological risks, and potential of antibiotic resistance. Environ Sci Technol. 2023;57:9474–94.
32. Ma H, Pu S, Liu S, Bai Y, Mandal S, Xing B. Microplastics in aquatic environments: Toxicity to trigger ecological consequences. Environ Pollut. 2020;261:114089.
33. Makumbura RK, Mampitiya L, Rathnayake N, Meddage DPP, Henna S, Dang TL, Hoshino Y, Rathnayake U. Advancing water quality assessment and prediction using machine learning models, coupled with explainable artificial intelligence (XAI) techniques like Shapley additive explanations (SHAP) for interpreting the black-box nature. Results Eng. 2024;23:102831. https://doi.org/10.1016/j.rineng.2024.102831.

34. Mekonnen MM, Hoekstra AY. (2016). Four billion people facing severe water scarcity. Sci Adv, 2(2), e1500323.
35. Naidu R, Biswas B, Willett IR, et al. Chemical pollution: A growing peril and potential catastrophic risk to humanity. Environ Int. 2021;156:106616.
36. Nearing GS, Kratzert F, Sampson AK et al. (2021). What role does hydrological science play in the age of machine learning? Water Resour Res, 57, e2020WR028091.
37. Nishat MH, et al. Comparative analysis of machine learning models for predicting water quality index in Dhaka's rivers of Bangladesh. Environ Sci Europe. 2025;37. https://doi.org/10.1186/s12302-025-01078-w.
38. Kebede MM, Al Masud MA, Ortbal S, Shin WS, Mekonnen MM, Clement TP, Terry LG. Adsorptive removal of PFAS from aqueous solutions using GAC, PAC and ball-milled colloidal activated carbon: Characterizing efficiency, kinetics, and mechanisms. ACS ES&T Water. 2025;5(11):6554–66. https://doi.org/10.1021/acsestwater.5c00641.
39. Olawade DB, Wada OZ, Ige AO, Egbewole BI, Olojo A, Oladapo BI. Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions. Hygiene Environ Health Adv. 2024;12:100114.
40. Paíga P, Figueiredo S, Correia M, André M, Barbosa R, Jorge S, Delerue-Matos C. Occurrence of 97 pharmaceuticals in wastewater and receiving waters: Analytical validation and treatment influence. J Xenobiotics. 2025;15(3):78.
41. Persson L, Carney Almroth BM, Collins CD, et al. Outside the safe operating space of the planetary boundary for novel entities. Environ Sci Technol. 2022;56(3):1510–21.
42. Petrie B, Barden R, Kasprzyk-Hordern B. A review on emerging contaminants in wastewaters and the environment: Current knowledge, understudied areas and recommendations for future monitoring. Water Res. 2015;72:3–27.
43. Prosser RS, Sibley PK. Human health risk assessment of pharmaceuticals and personal care products in plant tissue due to biosolids and manure amendments, and wastewater irrigation. Environ Int. 2015;75:223–33.
44. Rahman MF, Peldszus S, Anderson WB. Behaviour and fate of perfluoroalkyl and polyfluoroalkyl substances (PFASs) in drinking water treatment: A review. Water Res. 2014;50:318–40.
45. Rebryk A, Haglund P. Non-targeted screening workflows for gas chromatography–high-resolution mass spectrometry analysis and identification of biomagnifying contaminants in biota samples. Anal Bioanal Chem. 2020;413:479–501.
46. Richardson SD, Ternes TA. Water analysis: Emerging contaminants and current issues. Anal Chem. 2018;90(1):398–428.
47. Richardson K, Steffen W, Lucht W, Bendtsen J, Cornell SE, Donges JF, et al. Earth beyond six of nine planetary boundaries. Sci Adv. 2023;9:eadh2458.
48. Rockström J, Steffen W, Noone K, et al. A safe operating space for humanity. Nature. 2009;461:472–5.

49. Rockström J. Diagnosing earth's tipping points: Where we stand in the Anthropocene. Front Public Health. 2025;13:1653860.
50. Rout PR, Zhang TC, Bhunia P, Surampalli RY. Treatment technologies for emerging contaminants in wastewater treatment plants: A review. Sci Total Environ. 2021;753:141990.
51. Sakschewski B, Caesar L et al. (2025). Planetary Health Check 2025. Potsdam Institute for Climate Impact Research (PIK). https://doi.org/10.48485/pik.2025.017
52. Sauvé S, Desrosiers M. A review of what is an emerging contaminant. Chem Cent J. 2014;8:15.
53. Schwarzenbach RP, Escher BI, Fenner K, et al. The challenge of micropollutants in aquatic systems. Science. 2006;313(5790):1072–7.
54. Sela L, Sowby RB, Salomons E, Housh M. Making waves: The potential of generative AI in water utility operations. Water Res. 2025;272:122935.
55. Steffen W, Richardson K, Rockström J, Cornell SE, Fetzer I, Bennett EM, et al. Planetary boundaries: Guiding human development on a changing planet. Science. 2015;347:1259855.
56. Su J, Xu W, Lin Z. Algorithm for monitoring water quality parameters in optical systems based on artificial intelligence data mining. Sci Rep. 2024;14:28142.
57. Tadić Đ, Manasfi R, Bertrand M, Sauvêtre A, Chiron S. Use of passive and grab sampling and high-resolution mass spectrometry for non-targeted analysis of emerging contaminants and their semi-quantification in water. Molecules. 2022;27(10):3167.
58. Tong S, Bambrick H. Sustaining planetary health in the Anthropocene. J Global Health. 2022;12:03068.
59. Tushar MMR, Pushan ZA, Aich N, Rowles LS. Balancing sustainability goals and treatment efficacy for PFAS removal from water. npj Clean Water. 2024;7:130.
60. United States Environmental Protection Agency (USEPA). (2024). PFAS National Primary Drinking Water Regulation. Federal Register, 89 FR 32532 (April 26, 2024).
61. Vörösmarty CJ, McIntyre PB, Gessner MO, et al. Global threats to human water security and river biodiversity. Nature. 2010;467:555–61.
62. Wackett LP. Evolutionary obstacles and not C–F bond strength make PFAS persistent. Microb Biotechnol. 2024;17:e14463.
63. Wada OZ, Olawade DB. Recent occurrence of pharmaceuticals in freshwater, emerging treatment technologies, and future considerations: A review. Chemosphere. 2025;374:144153.
64. Walczak N, Walczak Z. Assessing the feasibility of using machine learning algorithms to determine reservoir water quality based on a reduced set of predictors. Ecol Ind. 2025;113556. https://doi.org/10.1016/j.ecolind.2025.113556.
65. Wang A-J, Li H, He Z, Tao Y, Wang H, Yang M, Savic D, Daigger GT, Ren N. Digital twins for wastewater treatment: A technical review. Engineering. 2024;36:21–35.
66. Wang Y, Liu G, Wang Y, Mu H, Shi X, Wang C, Wu N. The global trend of microplastic research in freshwater ecosystems. Toxics. 2023;11(6):539.

67. Whitmee S, Haines A, Beyrer C, et al. Safeguarding human health in the Anthropocene epoch: Report of the Rockefeller Foundation–Lancet Commission on planetary health. Lancet. 2015;386:1973–2028.
68. Wilkinson JL, Boxall ABA, Kolpin DW et al. (2022). Pharmaceutical pollution of the world's rivers. Proceedings of the National Academy of Sciences, 119(8), e2113947119.
69. Xie Y, et al. PFAS removal from reverse osmosis and nanofiltration brine by granular activated carbon: Thermodynamic insights into salinity effects. Water Research; 2025.
70. Yang Y, et al. Climate change exacerbates the environmental impacts of agriculture. Science. 2024;385:eado0688.
71. Yu Y, Wang S, Yu P, Wang D, Hu B, Zheng P, Zhang M. A bibliometric analysis of emerging contaminants (EC) (2001–2021): Evolution of hotspots and research trends. Sci Total Environ. 2024;907:168116.
72. Zaggia A, Conte L, Falletti L, Fant M, Chiorboli A. Use of strong anion exchange resins for the removal of perfluoroalkylated substances from contaminated drinking water in batch and continuous pilot plants. Water Res. 2016;91:137–46.
73. Zhang H, et al. Optimizing water quality index using machine learning: A six-year comparative study in riverine and reservoir systems. Sci Rep. 2025;15:10187.