ENVIRONMENTAL RESEARCH
WATER

PURPOSE-LED PUBLISHING™

Part of the ENVIRONMENTAL RESEARCH SERIES

PAPER • OPEN ACCESS

Water quality impacts on human health: towards an integrated, solution-oriented global assessment

To cite this article: Nynke Hofstra *et al* 2026 *Environ. Res.: Water* **2** 015009

View the article online for updates and enhancements.

ENVIRONMENTAL RESEARCH
WATER

OPEN ACCESS

RECEIVED
30 June 2025

REVISED
11 December 2025

ACCEPTED FOR PUBLICATION
5 February 2026

PUBLISHED
16 March 2026

PAPER

Water quality impacts on human health: towards an integrated, solution-oriented global assessment

Nynke Hofstra[1,*], Martina Flörke[2], Edward Jones[3], Issoufou Ouedraogo[4], Joel Podgorski[5], Eirini Politi[6], Katrin Schweden[2], Stefan Simis[7], Kerstin Stelzer[6], Maryna Strokal[1], Michelle T H van Vliet[3] and Stijn Peeters[1]

1 Earth Systems and Global Change Group, Wageningen University, Wageningen, The Netherlands
2 Engineering Hydrology and Water Resources Management, Ruhr University Bochum, Bochum, Germany
3 Utrecht University, Utrecht, The Netherlands
4 Mining Engineering Department, University Yembila-Abdoulaye-TOGUYENI, BP 54 Fada N'Gourma, Burkina Faso
5 Eawag, Swiss Federal Institute of Aquatic Science and Technology, Dübendorf, Switzerland
6 Brockmann Consult GmbH, Hamburg, Germany
7 Plymouth Marine Laboratory, Plymouth, United Kingdom
* Author to whom any correspondence should be addressed.

E-mail: nynke.hofstra@wur.nl

Keywords: water quality, human health, integrated assessment, cumulative health impacts, global change

Abstract

Poor water quality negatively affects human health. Large-scale knowledge of present and future water quality and associated health impacts remains limited, hindering the development of effective policies and regulations to reduce water quality related health risks. This paper collates current knowledge on global water quality relevant for human health at present and in the future and identifies key knowledge gaps and ways forward. Six relevant water quality constituent groups include (1) microorganisms, (2) organic micropollutants, (3) heavy metals, metalloids and constituents of geogenic origin, (4) nitrate/nitrite, (5) salts/salinity, and (6) plastics. These have a variety of health impacts ranging from gastroenteritis to cancer. An analysis of monitoring data and approaches for past and future water quality and health risk demonstrates that data availability for the assessment of water quality impacts on human health is very limited, while integration of these approaches provides some opportunities to reduce knowledge and data gaps in this field. We call for an integrated, solution-oriented approach that should incorporate interactions between multiple constituents, study compound impacts on health, and focus on synergies and trade-offs of interventions that can improve human health. In addition, this approach should include human health alongside other impacts, such as animal health, aquatic ecosystems and food production. A holistic approach would provide more comprehensive understanding of present and future water quality and consequent human health impacts, which is a prerequisite for intervention strategies, and the realisation of sustainable development goals (SDGs) 6 for clean water and 3 on good health and well-being.

1. Introduction

Water quality plays a crucial role in maintaining human health, influencing both direct and indirect health outcomes (Schwarzenbach *et al* 2010, Boelee *et al* 2019, Lin *et al* 2022). Contaminated water is a major cause of waterborne diseases, including cholera, dysentery, and typhoid, which affect millions of people globally, particularly in low-income regions with inadequate sanitation infrastructure (WHO 2022). Chemical constituents, such as heavy metals (lead, arsenic, and mercury), pesticides, nitrates and various geogenic constituents (particularly in groundwater) have been linked to additional health risks, leading to long-term effects such as neurological disorders, developmental issues in children, and cancer (e.g. Gleick 2014). Nutrient pollution puts aquatic food web integrity at risk (Dai *et al* 2023), and toxin exposure from resultant bloom-forming phytoplankton can harm humans and wildlife (Pinto *et al* 2023). Furthermore, emerging constituents, including pharmaceuticals and microplastics, are increasingly being detected in water supplies, raising concerns about their potential long-term health implications (Barboza *et al* 2018).

The availability of clean and safe water for domestic use is essential for preventing diseases and promoting overall well-being. SDG 6 emphasises the need for universal access to clean water, safe drinking water and adequate sanitation by 2030 (United Nations 2015). However, challenges such as rapid urbanisation, industrialisation, intensified agricultural and irrigation, and mining activities threaten water quality and accessibility across the world. Climate change exacerbates water pollution by increasing the frequency of extreme weather events, such as rainstorms, floods, heatwaves and droughts, which disrupt water supply systems and promote the spread of constituents (Caretta *et al* 2022, Van Vliet *et al* 2023).

Water quality problems have been recognised but remain underrepresented in policy and regulations (Damania *et al* 2019, Desbureaux *et al* 2022). A main reason for this is the complex nature of this so-called wicked problem (Rittel and Webber 1973). This complexity is demonstrated by the wide range of constituents exist that influence the water quality of different types of water bodies, such as rivers, lakes, coastal waters and groundwater that also interact (e.g. legacy effects (Basu *et al* 2022)). Humans are exposed to these water bodies in different ways, depending on their location, livelihood, culture, wealth, and gender, amongst other factors. Important exposure pathways include drinking, bathing, ingestion during domestic use, eating vegetables or grains irrigated or washed with contaminated water, or aquatic plants (such as water spinach), eating contaminated fish and shellfish, and skin contact. Additionally, several key groups of constituents in water bodies that people are exposed to lead to a wide variety of health impacts (table 1). These constituents can interact, influencing their compounding health impacts (Koppe *et al* 2006, Genthe *et al* 2013). Moreover, some constituents influence human health directly, while others have more indirect effects, adding to complexity. Finally, in addition to the complexity of water quality impacts on health, which should consider constituents, water bodies, exposure routes, health impacts and interactions, there are wider social and governance dimensions of the problem, including socio-economic, financial capacity, legal and policy aspects (Wuijts *et al* 2018). The latter aspects are not considered here, though not for lack of importance.

While the links between water quality and human health are well established, there is currently no complete overview of the water quality impacts on human health. This overview is required, to understand how to improve water quality and public health. Due to the complexity of the problem, there is no single approach that can comprehensively improve water quality and public health. International and national policies and interventions to improve water quality and public health can prevent contamination, such as banning certain chemicals or expanding wastewater treatment. As a first step towards adequately regulating water quality and improving human health, we need to understand the problems and dynamics across scales (Damania *et al* 2019). As a priority, we require understanding of hotspot areas with high concentrations or disease burden, contamination sources, trends over time and exposure routes before suitable mitigation and adaptation measures can be proposed. However, at present, observational data on water quality for relevant constituents is scarce, particularly in areas where health impacts are largest (Jones *et al* 2024b). First large scale (continental, global) modelling studies for water quality on relevant constituents exist, but are rarely linked to health impact assessments.

In order to advance the assessment of the impact of water quality on human health, which is essential to move towards policy and regulation, the objective of this paper is to collate the current knowledge on water quality relevant for human health both at present and in the future, and to identify knowledge gaps and ways forward. This paper addresses this objective from a large scale perspective (continental, global). We first list water quality constituents relevant for human health. Subsequently, we evaluate data availability from *in situ* observations, remote sensing and modelling for present day water quality. We then study opportunities to evaluate future water quality and the link between water quality and human health. We end the paper with lessons learned and a way forward to assess the impact of water quality on human health.

2. Water quality constituents and their health impacts

The scientific literature converges on a core set of water quality constituents that influence human health in different ways (table 1). Some constituents influence human health acutely, while others require long-term exposure. An example of an acute impact is diarrhoea caused by pathogens after exposure to contaminated drinking water. Examples of impacts caused by long-term exposure are dental and skeletal fluorosis and arsenicosis, including heart disease and various cancers, due to the presence of fluoride (Ayoob and Gupta 2006) and arsenic (Rahman *et al* 2009) in drinking water. These conditions significantly impact the quality of life in affected populations. Most constituents also cause indirect effects. Nitrate, for example, can directly cause blue baby syndrome and is also an important factor in the development of (toxic) algal blooms and therefore indirectly linked to gastroenteritis or supporting populations of *Vibrio cholerae* bacteria (Epstein 1993). The latter examples also demonstrate links or interactions between water constituents. Many more interactions may occur, such as several constituents that share the same sources, including human and zoonotic microorganisms, nitrate and antibiotics that are emitted by agriculture and sewer systems. Additionally, microplastics may provide a surface for biofilms that can transport human and zoonotic microorganisms (Kooi *et al* 2017, Wang *et al* 2021, He *et al* 2022). These and other interactions should be considered in an overall assessment of water quality relevant for human health, but are not the focus of this paper.

We distinguish six main constituent groups of water systems directly relevant for human health: (1) microorganisms, (2) organic micropollutants, (3) heavy metals, metalloids and constituents of geogenic origin, (4) nitrate/nitrite, (5) salts/salinity, and (6) plastics (table 1). Microbial contamination consists of human and zoonotic microorganisms including viruses such as norovirus, bacteria such as *Salmonella*, protozoans such as *Cryptosporidium* and helminths such as *Ascaris*, antimicrobial resistant microorganisms (AMR), algae and cyanobacteria. Gastroenteritis is a key impact of microbial contamination, but the impacts are much more diverse. *V. cholerae* in water is an example of an important bacterium and an important contributor to the annual 1.4–4.3 million cholera cases that continue to occur globally (Ali *et al* 2012, Momba and Azab El-Liethy 2017). Lack of access to clean water results in higher rates of diarrheal diseases, which are among the leading causes of child mortality in developing countries (Prüss-Ustün *et al* 2019, Kyu *et al* 2025). AMR is of particular concern (WHO 2015), because infections with AMR microorganisms are often much more difficult to treat than infections with microorganisms that are not resistant. Water is an important factor in the spread of AMR, although its role has not yet been quantified (Larsson *et al* 2018). Cyanobacteria can form biotoxins and when they bloom, can result in closure of bathing water sites to prevent toxic effects, including skin irritation and gastroenteritis (Backer *et al* 2015).

A wide variety of different organic micropollutants originate in manufacturing, agriculture, and human waste and, when discharged to the water, pose a health risk to the population (Landrigan *et al* 2018). Examples of these organic micropollutants include pesticides (Zhang *et al* 2024), pharmaceuticals (Zhang *et al* 2025) and per- and polyfluoroalkyl substances (PFAS) (Gander 2025). Emerging organic micropollutants are continuously introduced in water resources (Wołowicz and Munir 2025). Exposure to the organic micropollutants can result in a variety of impacts, including disruption of the endocrine, reproductive and immune systems, and they are able to cause behavioural problems, cancer, diabetes and thyroid, kidney and liver problems (Schwarzenbach *et al* 2010, Fenton *et al* 2021).

Heavy metals, metalloids and other geogenic constituents originating from the Earth's crust can accumulate naturally through geogenic processes in surface and groundwater and have been introduced by anthropogenic processes including agriculture and industrial production (Bradl 2005). Around 30 of the 92 metals and metalloids potentially affect human health, because they are toxic (Morais *et al* 2012). Arsenic is one of the toxic metalloids that is widely present in groundwater. It can lead to skin, vascular and nervous system disorders and cancer (Hughes 2002). The widespread nature of arsenic leads to an estimated 92–220 million people that have been exposed to high arsenic concentrations in groundwater (Podgorski and Berg 2020).

The impacts of nitrate have been provided in the first paragraph of this section. Wang *et al* (2023) used the global nutrient model (GNM) and nitrate monitoring data showing an increase in world population exposed to high surface-water nitrate during 1970–2010. High salinity of water for drinking water can contribute to hypertension, kidney disease, and gastrointestinal distress, especially in vulnerable populations (Khan *et al* 2020).

Plastic pollution of water systems has been studied intensively over the past decades, but its impacts on human health are still not well-understood (Rist *et al* 2018, Prata *et al* 2020). Also the role that water plays in human health risk assessments is unclear (Koelmans *et al* 2019). One of the reasons is that it is not always known which additives and chemicals are used to produce plastics. The toxic effects of those chemicals may differ. Some impacts of plastics on accelerating planetary boundaries have been discussed (Villarrubia-Gómez *et al* 2024) with indirect links to human health (e.g. through aerosols and water pollution).

Table 1 does not list water temperature as a constituent affecting human health. However, it affects other health related water quality constituents, such as pathogens or plastics. Elevated water temperatures are often associated with harmful algal blooms and bacterial growth, causing illness and creating risks for recreation and domestic water use. Regardless, algal blooms can be equally formed from species that are optimised for growth at lower temperatures, thus presenting a global health risk (Reinl *et al* 2023).

3. Monitoring strategies for past and present water quality

Many water quality constituents relevant for human health have been studied, although data availability is limited at the large scale (table 1). In this section we evaluate the availability of monitoring data for global water quality assessment relevant for human health. Monitoring data include *in situ*, remote sensing, and modelled data. For some constituents, such as arsenic, *in situ* groundwater quality monitoring data are available, while for others, such as microorganisms, surface water quality data are more abundant (Jones *et al* 2024b). For AMR bacteria and/or genes the spread across the world has been explored in the past in epidemiological or burden of disease studies (Murray *et al* 2022, Naghavi *et al* 2024) and water is highlighted to have an important role in spreading antimicrobial resistance (Sambaza and Naicker 2023). However, as far as the authors are aware, no large-scale overview of water quality for AMR is available at the time of writing.

Each information source has its own purpose, strengths and weaknesses (table 2). *In situ* observations provide the most diagnostically relevant observations of water quality and can often be traced to analytical standards. The advantage of *in situ* observations is that they provide actual water quality information for a certain time and place, with the potential to quantify uncertainties of sampling and laboratory analysis. *In situ* data can be used to evaluate the performance of water quality models. However, we can, unfortunately, not sample every relevant water body at every moment in time, and laboratory analysis takes time, meaning that near-real-time interventions are not always possible.

Remote sensing methods provide water quality estimates for certain times and locations. They are more continuous in space and time than achieved with *in situ* observation methods and, while data gaps remain, are more readily adapted to train and validate models. The majority of remote sensing relevant to water quality monitoring is optical in nature, and has as its main disadvantage that it is constrained to a limited number of water quality constituents; mostly visible contamination, such as algal and cyanobacteria blooms. For other constituents, optical remote sensing can be used to help develop input data for models, or to extrapolate pollution through correlation with observable substances such as sediments transported by rivers. Combinations of remote sensing techniques can be useful too, for instance, by identification of source locations for contamination, such as waste water treatment plants (WWTP) using thermal remote sensing to identify temperatures relevant for degradation of constituents, or by studying lake and reservoir water volumes that determine water residence time and dilution from satellite altimetry (using radar), which are main factors determining biological and chemical water quality. The quantity and quality of groundwater is almost entirely out of reach of satellite and airborne observation, with the exception of (gravity recovery and climate experiment)-based groundwater quantity change detection based on satellite remote sensing at very coarse spatial resolution ($\sim$300 km) and monthly intervals (Tapley *et al* 2002).

Model outputs include those that are continuous in space (including depth) and time, with time step and spatial resolution variable between models. These modelled data are outputs of statistical or process-based water quality models. Mechanistic models, such as those that combine hydrological and biogeochemical interactions, use generally available input data, such as data sanitation systems, wastewater treatment plants, animal numbers, environmental conditions, and constituent concentrations in these systems, together with statistical equations or mathematical understanding of processes to simulate water quality. Models are the only data type that can be cautiously used to anticipate future changes in water quality and can be calibrated an/or validated using *in situ* and remote sensing data. The uncertainty of model outcomes can be high and suffer from limited availability of relevant *in situ* or remote sensing data. The uncertainties, however, can be evaluated using different ways to enhance trust in the models (Strokal *et al* 2024).

3.1. *In situ* observations

In situ measurements are fundamental to our understanding of water quality dynamics and quantification of risks to human health, while also underpinning the development and evaluation of modelling and remote sensing approaches. However, large diversity exists in the availability and accessibility of observational water quality data relevant for human health across different constituents, water body types and world regions (Jones *et al* 2024b). To demonstrate the availability of water quality data for human health, here we focus on four of the six critical constituent groups: (1) microorganisms (faecal coliform (FC), *E. coli*); (2) heavy metals, metalloids and constituents of geogenic origin (arsenic, cadmium, chromium, copper, fluoride, lead, mercury, potassium, zinc); (3) nutrients (nitrate, nitrite);

Table 1. Water quality constituents relevant for human health, together with human health impacts, constituent sources, indicators and thresholds for drinking, recreation, and irrigation water. This list is non-exhaustive, as no detailed literature review has been performed. For the last column, font format refers to data availability and is as follows: italics font: GEMStat or other large-scale databases (Jones *et al* 2024b), normal font: remote sensing, underlined font: modelling, and italics and underlined font refers to a combination of GEMStat and modelling. Normal font is for surface water, bold font for groundwater. This font format overrules the italics formatting for some microorganisms. The table is adapted from the United Nations Environment Programme (UNEP) World Water Quality Alliance (WWQA) Baseline Assessment Report. Reproduced with permission from (World Water Quality Alliance 2021).

Water quality constituent	Impact: Direct	Impact: Indirect	Sources	Indicator for which data are available at large scale[a]
Microorganisms, including: -human and zoonotic microorganisms (viruses, bacteria, protozoa and helminths), - antimicrobial resistant (AMR) microorganisms and - (toxic) algae/cyanobacteria	- Acute and chronic gastroenteritis, fever, mortality, hepatitis, pneumonia, cancer, among others (Aw 2018). - Reduced ability to treat infections (Kiulia *et al* 2015). - Producing toxins that cause gastroenteritis (Codd *et al* 1999), respiratory failure (Metcalf and Codd 2009), neurological disorders (Linares *et al* 2024), skin infections, allergies (Dhillon and Rowlins 2025).	- Stunting, learning deficits, food safety threatened (Aw 2018) - Former diseases become problem once again (WHO 2015). - Stunting, bioaccumulation risk, substrate or carriers for disease vectors (Caller *et al* 2009), reduce UV damage to pathogens by shielding, health impacts after eating fish and shellfish (Grattan *et al* 2016)	- Human faeces, livestock manure, wildlife - Human faeces, livestock manure, presence of antimicrobials in the environment - Largely autochthonous production, elevated by eutrophication	*Faecal coliforms (Jones et al 2023; UNEP, 2016)* *E. coli* Vibrio cholerae (Racault *et al* 2019). Cryptosporidium concentrations (Vermeulen *et al* 2019). Rotavirus loads (Kiulia *et al* 2015). Phytoplankton biomass or chlorophyll-a pigment (Copernicus Land Monitoring Service & Copernicus Land Monitoring Service Helpdesk, 2024a, 2024b) Cyanobacteria biomass concentrations (Carrea *et al* 2022; Copernicus Land Monitoring Service, & Copernicus Land Monitoring Service Helpdesk 2024a, 2024b).
Organic micropollutants (e.g. pesticides, pharmaceuticals, persistent organic pollutants (POPs), per- and polyfluoroalkyl substances (PFAS) and many others)	Disruption of the endocrine, reproductive and immune systems, behavioural problems, cancer, diabetes, thyroid, kidney and liver diseases (Fenton *et al* 2021; Landrigan *et al* 2018; Mishra *et al* 2022). Direct effects due to pharmaceuticals in drinking water are very unlikely (de Jesus Gaffney *et al* 2015; WHO 2012).	Use of anti-microbials can cause AMR, bioaccumulation risk	Pesticides: agricultural use, home/garden use Pharmaceuticals: medical use, home and agricultural medical use, Other: specialised chemicals in manufacturing	Insecticide runoff (Ippolito and Fait 2019). Glyphosate and its AMPA loads (Zhang *et al* 2024). Antibiotics loads (Aus der Beek *et al* 2016; Zhang*et al* 2025)

(Continued.)

Table 1. (Continued.)

Heavy metals, metalloids and constituents of geogenic origin	Skin, vascular and nervous system disorders and cancer (Hughes 2002). Dental and skeletal diseases (International Programme on Chemical Safety 2002) Neurotoxicity (Ijomone *et al* 2020) Cancer, other toxic effects, diarrhoea and vomiting (Chowdhury *et al* 2016)	Food quality and safety threatened	Arsenic, fluoride and manganese: primarily natural sources, also from mining activities and pesticides Other heavy metals: Manufacturing, agriculture, domestic wastewater, atmospheric deposition, leakage from pipes (Chowdhury *et al* 2016).	***Arsenic concentrations (Podgorski and Berg 2020). Fluoride concentrations (Amini et al 2008; Podgorski and Berg 2022). Heavy metal concentrations (Kumar et al 2019).***
Nitrite/nitrate	Blue baby syndrome (Canter 1996) colorectal cancer, bladder, and breast cancer and thyroid disease (Ward *et al* 2018).	Impacts of toxic algal blooms (Backer *et al* 2015).	Land application of nitrogen from manure, sewage or industrial sludge, septic systems, geologic nitrogen mobilised by irrigation water (Canter 1996). For surface water also human waste and discharge of animal manure from livestock production (only in China), use of synthetic fertilisers, atmospheric N deposition (M. Strokal *et al* 2016).	*Nitrate concentrations (Ouedraogo and Vanclooster 2016). Dissolved inorganic nitrogen loads (Micella et al 2024)*
Salts/salinity	Hypertension, increased risk of (pre)eclampsia infant mortality (Shammi *et al* 2019).	Food quality and safety threatened	Irrigation return flows, domestic waste water, manufacturing (Thorslund and van Vliet 2020)	*Salinity (TDS) (Jones et al 2023; Thorslund and van Vliet 2020)*
Plastics, incl. microplastics	Particle toxicity leading to oxidative stress, cell damage, inflammation, and impairment of energy allocation functions, toxicity of substances leaching out of plastic (Barboza *et al* 2018; Strokal *et al* 2019; Vethaak and Leslie 2016; Villarrubia-Gómez *et al* 2024), but unquantified	Habitat for pathogens and vectors that can spread infectious diseases (Amaral-Zettler *et al* 2021; Koelmans *et al* 2016; Liu *et al* 2024).	Personal care products, clothing fibres, car tire wear, macroplastics in mismanaged solid waste (van Wijnen *et al* 2018, 2019), agricultural plastic mulching and greenhouses (Khalid *et al* 2023)	Microplastics concentrations (van Wijnen *et al* 2019) and loads (Micella *et al* 2024) *Microplastics concentrations* (Li *et al* 2020)

[a] The indicator constituent here is the state of the water quality constituent for which data are available from GEMStat (https://gemstat.org) or other large-scale databases, or from remote sensing or models from the ISIMIP consortium for large spatial scales from continents to global (Strokal *et al* 2025).

Table 2. A summary of strengths and weaknesses of the monitoring methods *in situ* observations, remote sensing observations and model outputs.

	In situ observations	Remote sensing observations	Model outputs
Strengths	• Provide actual water quality at a certain time and location • Uncertainties of sampling and laboratory analysis can be quantified • Can be used to calibrate and evaluate the performance of water quality models	• Provide water quality estimates for a certain time and location • They are more continuous in time and space than *in situ* observations • Can be used to calibrate and evaluate the performance of water quality models • Provide input data for models, such as source locations like WWTPs, temperature for decay or degradation processes or using volumes to determine residence time • Some visual characteristics can be used as proxy for contamination	• Provide spatially and temporally continuous water quality estimates • Mechanistic, uncalibrated models use generally available input data to simulate water quality • Can be cautiously used in scenario analyses to project future changes • Uncertainties can be quantified by different methods to enhance trust in models, and can be quantified when monitoring data are available.
Weaknesses	• Not every relevant water body can be sampled at every moment in time • Near real-time observations are often time-limited by lengthy and potentially costly laboratory processes	• Data gaps remain • Remote sensing is due to its optical nature limited to a selected number of constituents, including visual contamination, such as algal blooms and turbidity. • Groundwater quality is almost entirely out of reach	• Statistical models and calibrated mechanistic models depend on *in situ* or remote sensing observations • Model output is subject to uncertainties in model input datasets (e.g. climate forcing, land use, location of pollution sources etc.) • *In situ* or observational data are required for validation • Uncertainties can be large and

and (4) salinity (total dissolved solids (TDS), electrical conductivity) (figure 1). For the other two groups, microplastics and organic micropollutants, data availability is limited. The data used for this analysis come from Jones (2024), who collated them from large-scale databases that are openly available. An approach to collect more data, in particular for underrepresented areas, could involve a systematic literature review of the scientific literature and government documents on local and regional water quality, such as performed for Lebanon (Sharif-Askari *et al* 2025).

3.1.1. Surface waters

Frequent sampling of surface waters is essential due to their sensitivity to seasonal variations (e.g. discharge, water temperature), in addition to strong connectivity with external factors (e.g. runoff, anthropogenic effluents) that can cause high variability in pollutant concentrations. According to this database, surface waters in North America are overwhelmingly the most intensely monitored for all four pollutant sub-groups, accounting for 77%, 57%, 57% and 46% of indicator bacteria, heavy metals, nutrients and salinity observations, respectively. Western Europe accounts for a substantial proportion of *in situ* observations of both nutrients (22% global share) and heavy metals (24%) are also substantial for Western Europe, while the number of measurements of salinity is high in East Asia & Pacific (38%) and of indicator bacteria in the Latin America & Caribbean (14%) regions. Consistently across all sub-groups, the number of measurements from the Middle East & North Africa (0.04% of total observations), Southern Asia (1.5%) and Eastern Europe and Central Asia (2.9%) are extremely low.

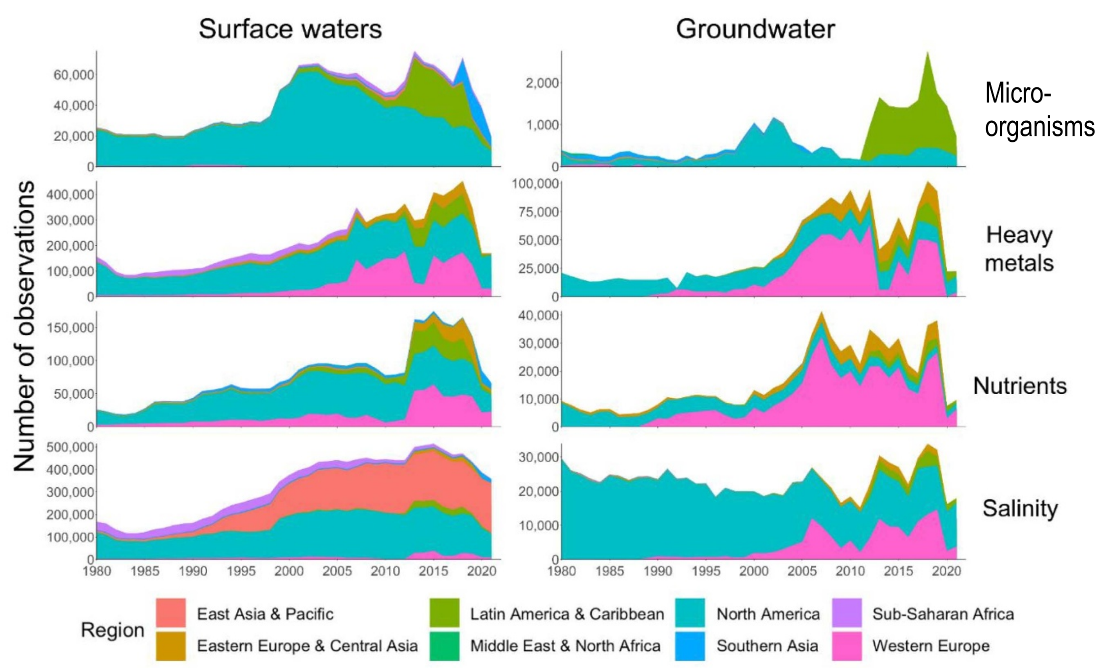

Figure 1. Regional distribution in the number of water quality measurements per year, separated for surface waters and groundwater and aggregated across four sub-groups of key relevance for human health: (1) microorganisms (faecal coliform, *E. coli*); (2) heavy metals, metalloids and constituents of geogenic origin (arsenic, cadmium, chromium, copper, fluoride, lead, mercury, potassium, zinc); (3) nutrients (nitrates, nitrite); and (4) salinity (total dissolved solids, electrical conductivity) based on data by Jones *et al* (2024b).

3.1.2. Groundwater

Compared to surface waters, there are significantly fewer measurements of groundwater quality in most regions globally. This can be attributed to factors including limited accessibility and visibility, economic costs and weaker regulatory oversight, but also less frequent sampling as concentrations tend to be more stable over time. Nevertheless, the global distribution of groundwater quality observations reflects the patterns in surface water quality data. For example, 86% of all observations were taken in just North America (47% of total observations) and Western Europe (38%) alone, with Western Europe particularly rich in observations of nutrients (57%) and heavy metals (44%) while North America is dominant in terms of measurements of salinity (79%). Very few measurements of groundwater quality are available across large parts of the world, with sub-Saharan Africa, the Middle East & North Africa, East Asia & Pacific and Southern Asia combined accounting for <0.5% of total observations. It should also be noted that observations of indicator bacteria are extremely rare across all world regions, with just ~30 000 measurements available globally from 1980–2021.

3.2. Remote sensing observations

Various domains of remote sensing can contribute directly and indirectly to the management of water resources and human health (Sengupta *et al* 2025). For surface water, optical sensors are now very commonly used to observe variations in water colour. Water, being transparent in the visible light spectrum, reflects very low light levels to remote sensors which therefore need to be highly sensitive over a wide dynamic range. This is typically the domain of so-called 'ocean-colour' sensors, which presently provide daily global observations at medium resolution (300 m equivalent pixel width), resolving water colour in water bodies down to a few square kilometres in surface area. Several 'land and water' sensors now also exist with even higher spatial detail (10–60 m per pixel), although care must be taken when clear waters are observed as their low reflectance can be at the noise level of these sensors (Jorge *et al* 2017, Clerc *et al* 2024). Additionally, the presence of nearby land can influence the appearance of water bodies in the satellite image through mixing of reflected light from land and water in the Earth atmosphere (Santer and Schmechtig 2000, Paulino *et al* 2022), in which case smaller spatial detail will not overcome the physical limitations of the observation, and advanced numerical reconstruction techniques are needed to interpret water colour.

Water colour is interpreted primarily in terms of biological and biogeochemical substance concentrations, broadly speaking those substances that colour the water. Being a mixed medium, the light absorption and scattering properties of dissolved and particulate substances jointly contribute to the observed colour at the surface, again requiring models or algorithms to disentangle these. At present, mature optical water quality products of the dominant colouring agents include chlorophyll-a pigment as a proxy of phytoplankton biomass, turbidity caused by suspended particles (whether organic or inorganic) and coloured dissolved organic matter. Their maturity is demonstrated in a number of operational data services in the marine and inland water domain, for example within the European Copernicus programme (see Copernicus Marine service: https://marine.copernicus.eu/ and Copernicus land monitoring service: https://land.copernicus.eu/). Direct observation of nutrients is largely out of reach, as few remote sensors are capable of recording reflected light in the ultraviolet range where e.g. nitrates contribute significantly to light absorption, and algorithms to deconvolve these signals using remote sensing observations are consequently lacking. Instead, modelling the relationships between phytoplankton biomass and organic carbon, nitrogen and phosphorus, may provide indirect insight into nutrient dynamics (Politi and Prairie 2018). Even given these limitations, it should be obvious that the observable light quality in surface waters bears direct relation to the survival of potential pathogens: ultraviolet light is rapidly absorbed by dissolved and suspended substances in water, but not in clean, clear water.

The most prominent, globally observable trend in water quality is the eutrophication of surface water bodies resulting in enhanced biological production and shifts in phytoplankton community composition. Phytoplankton can serve as a substrate for pathogens, with e.g. *Vibrio cholerae* concentrations correlating with remotely observable algal biomass indicators in affected inland waters (Racault *et al* 2019, Anas *et al* 2021, King *et al* 2022). Cyanobacteria blooms in surface waters are temporally and spatially variable. Regulatory monitoring involves collecting *in situ* water samples followed by light microscopy to determine species or group-level cell numbers, alongside nutrient concentration analysis (Poikane *et al* 2015). In general, lakes and reservoirs in Europe are sampled between three times over the entire summer season up to every two weeks for bathing water sites, increasing to once a week at maximum in case thresholds of a bloom are already passed (Papathanasopoulou *et al* 2019). Peak bloom events can occur over just several days, much shorter than the interval between *in situ* sampling. Moreover, water quality in lakes can show large horizontal differences within one lake, both in terms of light and nutrient availability and resulting phytoplankton biomass. Some bloom-forming cyanobacteria form cells that are naturally buoyant, which under calm weather may lead to accumulation at or near the water surface, such that wind and currents may introduce further patchiness. Localised surface scum events are readily observable using satellite observation (Matthews *et al* 2012, Matthews and Odermatt 2015).

In recent years, owing to the operational availability of satellite sensors, remote sensing has become a viable complement to global-scale monitoring of optical water quality. This has resulted in support for the understanding that (surface) blooms of cyanobacteria are on the rise globally as a result of climate change and land use practices (Huisman *et al* 2018, Wang *et al* 2025).

3.3. Model outputs

3.3.1. Surface water

Various global surface water quality models have been developed by the large-scale water quality modelling community, united in the inter-sectoral impact model intercomparison project (ISIMIP) water quality sector and the water quality modelling workstream of the world water quality alliance (WWQA), which includes several of the co-authors of this paper. Commonly, the large-scale water quality models simulate the flow of constituents through the environment. They incorporate the loading of the contaminants into the water body from domestic wastewater, agriculture and/or manufacturing. Afterwards, the constituents are followed throughout the water body and decay or degradation processes are incorporated. Global models cover a diverse set of different modelling approaches in terms of laws and assumptions using data-driven approach versus process-based approaches. They differ in the extent to which surface water quality models allow for temporal variability (static (simulating one or more specific timesteps separately) versus dynamic (simulating a period with a specific timestep while including dynamic processes and legacy effects) models) and spatial variability within river (sub) basins (spatially distributed versus lumped approaches). Examples are the dynamic spatially distributed models such as DynQual and WorldQual and static and lumped models such as MARINA. The models in the ISIMIP data archive cover the years 2005–2100, incorporating scenarios closely linked to the generally used climate scenarios, the shared socio-economic pathways (SSPs) and the representative concentration pathways (RCPs) combined here as SSP1-RCP4.5, SSP3-RCP7 and SSP5-RCP8.5 (see section 4). Their temporal resolution is from daily to annual (for the static models for one or more particular year(s)), and their spatial resolution varies between ~10 × 10 km per grid cell, ~50 × 50 km per grid cell to sub-basin and basin level. Appendix and section 2.1 in Strokal *et al* (2025) in this special issue provide more model details.

The water quality data archive (https://data.isimip.org/) of ISIMIP provides modelled water quality in terms of loads and/or concentration data. For instance, global models provide data for water temperature, nutrients (considering different nutrient forms), micro- and macro-plastics, chemicals (e.g. triclosan), microorganisms (e.g. cryptosporidium and FC as a coarse pathogen indicator), organic pollution as indicated by biological oxygen demand (BOD) and salinity indicated by TDSs or electrical conductance of surface waters. Most of these water quality constituents are directly relevant for human health. Some water quality constituents such as water temperature and salinity may affect concentrations of other water quality constituents (e.g. microorganisms or microplastic), important for human health.

Global simulations of nutrients are provided in the ISIMIP archive by various models such as IMAGE-GNM, MARINA, SWAT, GREEN, mQM and WorldQual. Plastics by the MARINA-Plastics model (Strokal *et al* 2023; Micella *et al* 2024) and microorganisms (pathogens or pathogen indicators) are provided by the GloWPA, WorldQual and DynQual models. Organic pollution (BOD) is represented by GREEN, WorldQual and DynQual, and surface salinity (TDS) by WorldQual and DynQual (Strokal *et al* 2025). In addition, water temperature is simulated by DynQual, CwatM and WorldQual using either process-based (mechanistic) or data approaches (Jones *et al* 2025). Using results from multiple surface water quality models (e.g. MARINA-Multi (Micella *et al* 2024) or DynQual) can help to provide more robust estimates of water quality hotspots that pose potential human health risks. Please see appendix 1 for model abbreviations, a brief overview of the models and references to model explanations.

One aspect of water pollution is the microbial pollution of surface waters, which has been shown to have a significant impact on public health (Rytkönen *et al* 2024). Notable examples of such pathogens include Cryptosporidium, a major cause of childhood diarrhoea and mortality (Choy and Huston 2020), and FC bacteria, a more prevalent indicator of microbial pollution (National Research Council (U.S.). Committee on Indicators for Waterborne Pathogens 2004). As an example, data for microorganisms have been qualitatively compared for the present day situation. Areas of high population density on all continents (except for Australia) have been identified as sites of pollution hotspots characterised by elevated concentrations of cryptosporidium and FC (as simulated by GloWPa-Crypto (Vermeulen *et al* 2019), WorldQual (UNEP 2016) and DynQual (Jones *et al* 2023). This finding suggests that human faeces constitute the predominant source of microbial pollution loadings.

3.3.2. Groundwater

Groundwater quality has traditionally been spatially modelled through interpolation, such as gridding or kriging (Machiwal *et al* 2018). However, these geospatial techniques become increasingly ineffective as the density of sampling (*in situ*) data points decreases. An alternative approach that has been steadily gaining popularity is the use of machine learning to predict groundwater quality parameters based on spatially continuous predictor variables. In addition to being less dependent on the spatial distribution of sampling points, the statistical relationships determined through modelling can provide useful and unexpected insights into the processes involved in the accumulation of the modelled parameter (Podgorski and Berg 2020). For geogenic (or naturally present) constituents, predictor variables relating to the natural environmental conditions are generally used, typically including geology, soil, climate and topography. Likewise, the modelling of anthropogenic constituents also includes other variables related to land use or population density. Although global models of groundwater quality exist for arsenic (Podgorski and Berg 2020) and fluoride (Podgorski and Berg 2022) models for other constituents, where available, are generally at the country to regional level.

3.4. Integration of *in situ* observations, remote sensing and models

All established means to observe, *in situ* and remotely, or model water quality have clearly stated limitations either of cost, transferability, or observation uncertainties. We may, therefore, consider whether the sum of these parts is likely to result in better assessment of water quality for health. However, as previous sections have laid out, fundamentally different properties of water quality are recorded through *in situ* sampling of biological, chemical and physical observations, remote physical observations and modelled data. To harmonise these data streams with spatial and temporal scale mismatches and widely varying volumes, continuity, latency, and measurement uncertainties, requires development of dedicated data scientific approaches.

Integration of the different data types has been proposed by WWQA (World Water Quality Alliance 2021) and described in the GlobeWQ report (Schmidt *et al* 2023). The integration, called triangulation in the GlobeWQ report, of all three data types, was performed for a case study in Lake Victoria.

Human health risks due to harmful cyanobacteria blooms have been reported in Lake Victoria and there is a need for improved understanding on the occurrence of these harmful blooms. Additionally, more information on the sources of contamination is required in order to develop strategies to reduce the occurrence of harmful blooms (Schmidt *et al* 2023). For this case study, the *in situ* data provided an understanding of the long term history of water quality in the lake. The remote sensing data provided insights in the chlorophyll *a* and harmful algal bloom indicators for the lake, covering the full lake and short lead times. Modelled data provided understanding on long-term loadings of constituents, such as phosphorus, into the lake from tributary catchments. Using these three data sources together, high chlorophyll *a* concentrations for Wiban Gulf in Lake Victoria could be attributed to high nutrient loadings received from two particular catchments, Nyando and Sondu, among other causes (Schmidt *et al* 2023). Management can, therefore, focus on reducing nutrient loadings in those two catchments.

This example for Lake Victoria shows that the integration of different data sources provides more insights than each of the three data sources individually. For the large scale, opportunities exist to use the three data types to improve our understanding and provide a solid basis for water quality management and impacts on human health.

In the future, using emerging innovations in data science, including artificial intelligence (AI), the authors envisage that more opportunities will emerge to develop statistical frameworks for data integration. AI approaches have, for instance, been used to evaluate overall water quality indices (Frincu 2025) and such indices could also be developed specifically for human health using different types of data sources. In all studies using large data volumes, it will, of course, remain important to ensure that the available data sources are representative of the variability in the system that is targeted by data-driven models. For data-driven modelling approaches, this may require frequent model re-training using updated reference data sets. These considerations are particularly relevant as datasets with variable observation bias gradually become mainstream (Liao and Naghizadeh 2023). Examples are targeted sampling efforts where agencies respond to foreseen risks (in a digital twin context), as well as citizen science where the specific motives for reporting observations at a given time and place are less well known.

4. Future water quality forecasts and projections

To better understand the impacts of socio-economic development and climate change on water quality, and to evaluate the effectiveness of interventions, long-term (up to 2050 or 2100) future water quality projections are essential. Additionally, short-term scenario forecasts, such as those used for early warning, can prevent human health impacts.

In recent years, considerable effort has been dedicated to impact studies concerning the future of water resources regarding quantity (e.g. ISIMIP). The modelling of future water quality demands a range of input data, including hydrological, water use and socio-economic conditions, as well as data on the development of sanitation and future wastewater treatment and agricultural practices (e.g. information on livestock and manure production). To address this knowledge gap, the development of water quality scenarios is essential. A WWQA modelling working group has dedicated significant efforts to building storylines and deriving quantitative scenarios (Bouwman *et al* 2024). The community consensus (Strokal *et al* 2025) followed the SSPs (O'Neill *et al* 2014), climate projections from ISIMIP 2b and 3b (Frieler *et al* 2017, Lange *et al* 2022), and incorporated future sanitation and treatment (Van Puijenbroek *et al* 2015, 2023).

Three key water quality scenarios for the future have been determined. These follow SSP1, SSP3 and SSP5, each connected to a relevant RCPs that determine the level of climate change. The SSP1-RCP2.6 scenario describes a future with limited population growth and a strong focus on equity, sustainability and the environment. Specifically relevant for water quality, this scenario has the strongest progress in sewerage development, wastewater treatment and management of onsite sanitation systems. Additionally, livestock numbers decrease and manure management improves. Climate change is limited in this scenario. SSP5-RCP8.5 also has limited population growth, but strongly focuses on technology development and energy produced using carbon-based fuels. The focus in this scenario is not on the environment, but human health is important. In SSP5 there is strong progress in sewerage development, but wastewater treatment does not increase as strongly as in SSP1. The management of onsite sanitation systems shows moderate progress. While manure management improves comparative to SSP1, the livestock numbers increase much more due to a more meat-focussed diet. This scenario has the strongest climate change. SSP3-RCP7, which is only part of ISIMIP 3b, is a regionalised scenario, where all regions must produce their own food. There is strong inequality and the environment is not important. Sewage connection rates and waste water treatment are not expected to improve in this scenario and management of onsite sanitation systems is poor. Additionally, livestock numbers increase and manure management is

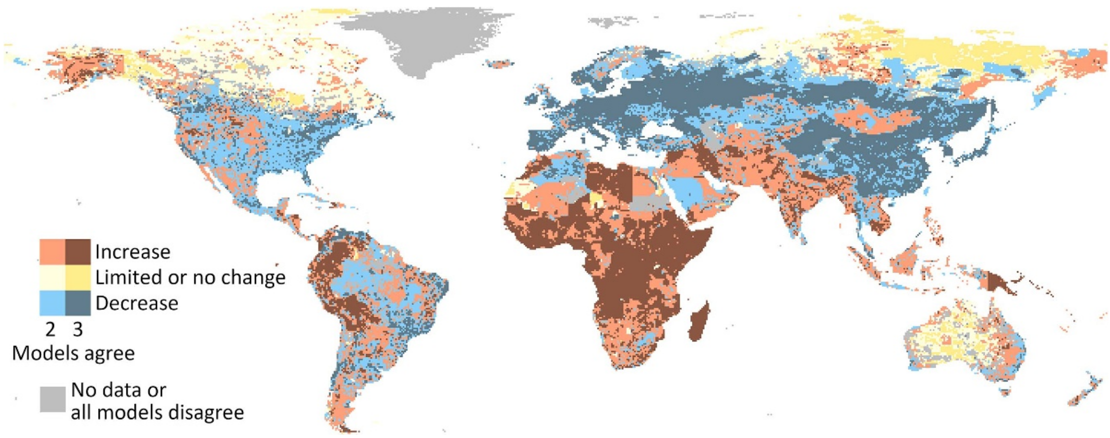

Figure 2. Agreement between models in future change of microorganism loads in surface waters. Data from the GloWPa-Crypto, DynQual and WorldQual models aggregated to 0.5° resolution have been used for the SSP5-RCP8.5 scenario for the year 2050 compared to 2015. The model output data for 2015 were subtracted from 2050. Afterwards, the data were divided in five quantiles. The data in the middle quantile was determined to have no or limited change, the data in the first two quantiles were determined to have a decrease, and the ones in the last two quantiles were determined to have an increase. The agreement between the models in having decrease, no or limited change, and an increase is provided in this Figure. Note: the modelled data were not fully normally distributed, but the median in the difference between 2050 and 2015 was for all models very close to 0 and the quantiles were deemed suitable.

not expected to improve. Climate change is strong, but not as strong as in SSP5, because the greenhouse gas emissions in SSP3 are reduced compared to SSP5 due to the more limited GDP (O'Neill *et al* 2014, Doelman *et al* 2018, Van Puijenbroek *et al* 2023). By studying how water quality relevant for human health changes for each of these scenarios, the potential future changes can be assessed. This provides insights into the possible trends over time, and also helps determine what is required to improve the water quality and reduce human health related impacts.

As an example of what is possible when an assessment is done for future water quality relevant for human health, in particular using multiple models for similar constituents, here we focus on microbial pollution. In order to project future microbial pollution loadings until the end of the century, model simulations were carried out with three global models (GloWPa-Crypto, WorldQual and DynQual). These models have been tested before (Reder *et al* 2017, Vermeulen *et al* 2019, Jones *et al* 2023, respectively). The model runs were performed on the scenario inputs developed within WWQA and available in ISIMIP, which have been explained in more detail in Strokal *et al* (2025) published in the same special issue. In this context, the model input and assumptions were set-up with input data representing the conditions of the SSP5-RCP8.5 scenario combination for 2050 compared to the baseline year 2015, simulated by all three models. As illustrated in figure 2, the ensemble modelling exercise reveals a high degree of model agreement in large regions worldwide, with two and often even three models providing the same projected change (increase or decrease). Notably, all considered models indicate an increase in microbial pollution loadings in Africa, while the models also show an increasing trend in India and the west coast of South America (with slight variation in the models that agree for the different grids). Conversely, a decreasing trend is indicated by the three models in vast regions of Europe and Asia, and by two models in China, the eastern regions of South America, and larger regions of the USA. The decreasing trends are associated with a decline or stable population growth, along with further improvements in sanitation practices and treatment levels, as projected under SSP5. The SSP5 projections indicate a decline in the number of individuals connected to primary treatment, while there will be an increase in those having access to secondary and tertiary treatment by 2050, driven by rapid technological progress. Even though SSP5 has the highest per capita income growth and significant investment in human health, not all regions benefit equally. An increase in microbial pollution entering rivers and streams is most likely to occur in sub-Saharan Africa and along the North African coastline. In Africa, the investment in and enhancement of wastewater treatment plants and treatment levels is inadequate in terms of keeping pace with urban population growth and the development of improved sanitation facilities (i.e. the access to reliable sanitation).

The high level of agreement observed in the model results across most regions of the world indicates the robustness of the model results in terms of trend development. The findings of this study offer insights into the pressure exerted on rivers and streams by microbial pollution. The increasing trends in microbial loadings pose a significant risk to human health and underscore the urgent need for increased investment in the construction of wastewater treatment plants and the enhancement of treatment levels. This is essential to prevent millions of people from contracting waterborne diseases.

In addition to long-term future projections, short-term forecasts can help prevent health risks, for example for cyanobacteria (Schaeffer *et al* 2022). Short-term forecasts can use observational data, such as remote sensing data, with statistical models to predict the occurrence of harmful cyanobacteria blooms in the order of days. Such forecasts can be coupled with daily advice on bathing water quality. In the case of Schaeffer *et al* (2022), the model provided the odds for a particular health alert level. These short-term forecasts provide more frequent updates than the weekly observed data, and therefore contribute to early warning for health risk and potentially reduced exposure and reduced human health risks.

5. The impact of water quality on human health

While the links between water quality and human health are well established, we currently cannot quantify the global disease burden that is directly or indirectly attributable to poor water quality. There would be several ways to do this, each of them with their own strengths and weaknesses, including uncertainties. The first way is to assess the results from epidemiological studies. Such studies, for instance, evaluate the disease burden of diarrhoea and link these to risk factors, such as unsafe drinking water, sanitation and hygiene (WASH). One of these studies concludes that around 1.4 million deaths and 74 million disability adjusted life years could have been prevented by safe WASH in 2019 (Wolf *et al* 2023). This value is also used in a publication summarising the disease burden due to water pollution (Fuller *et al* 2022), even though Wolf *et al* only focus on diarrhoea, acute respiratory infections, undernutrition and helminthiasis, which are not the only health impacts of water quality (table 1). Another study evaluates the number of cancer cases that were attributable to drinking water in countries with high access to safely managed water and finds that this number was 1.2 annual cancer cases per 100 000 population. However, this study also concludes that there was very little available data (Lee *et al* 2023). A first systematic literature review qualitatively summarises all epidemiological studies that relate water quality and health impacts (Lin *et al* 2022). They conclude that water quality has a huge impact on human health, although factors, such as country, region, age, and gender can influence this relation. However, a full epidemiological study that links the water quality to the disease burden does not currently exist and is not expected to become available in a short period of time, given the complexity of the multiple relevant constituents, the range of relevant water bodies, the wide variety in health outcomes, and the different risk factors.

The second way to study the disease burden related to water quality is by using health risk assessment, which simulates the health risks and resulting disease burden given the intake of or contact with a water source, the concentration of the contaminant in the water and dose response information (US EPA 1987, WHO 2021b). A large number of small scale risk assessments exist, mostly for individual water constituents and usually for a specific exposure route, such as drinking, swimming, and exposure to flood water. In recent years systematic literature reviews have become available that provide more generic risk and sometimes global estimates for, for example, microorganisms (e.g. Su *et al* 2024), heavy metals (e.g. Ma *et al* 2016), persistent organic pollutants (POPs) (e.g. Vasseghian *et al* 2021), etcetera. Conclusions include that the median health risks levels of pathogens exceed the thresholds. For heavy metal, traffic and land use are the primary factors for urban heavy metal loads and chromium, manganese and lead pose the highest health risks. For POPs, the concentrations were highest in surface waters compared to other water bodies and the highest health risks were found in South Africa. First approaches to determine health risks for emerging pollutants have been developed for microplastics (Senathirajah *et al* 2021) and antibiotic resistant bacteria (Ben *et al* 2019).

A first estimate for the disease burden related to diarrhoeal disease caused by *Cryptosporidium* in drinking water produced from surface water in sub-Saharan Africa, where risk assessment was linked to modelled surface water quality, showed that the countries with the highest disease burden also had relatively high HIV/AIDS prevalence and that the people consuming surface water directly also contributed most to the disease burden (Limaheluw *et al* 2019). Using modelled concentrations as input for health risk assessments provides opportunities, as this enables spatially continuous evaluation and identification of hotspots where research efforts should be focused, understanding of sources of water quality and important exposure pathways, and future scenario analyses. The scenario analyses can include, for instance, the impact of climate change on human health risk affected by water quality, or the effectiveness of interventions.

The third way to link water quality and health impacts is by comparing water quality concentrations from *in situ* observations, remote sensing or models to thresholds or standards for water quality. For many of the water quality constituents such thresholds exist, such as a maximum of 10 μg l^{-1} for arsenic, 1.5 mg l^{-1} for fluoride or 50 mg l^{-1} for nitrate in drinking water (WHO 2022), or 40 cfu/100 ml for the 95th percentile of enterococci concentrations in recreational water (WHO 2021a). For instance, for arsenic (Podgorski and Berg 2020) and fluoride (Podgorski and Berg 2022) in groundwater such analyses exist, demonstrating that 94–220 and approximately 180 million people are potentially affected by arsenic and fluoride, respectively, and the majority of these people live in Asia and Africa. Such an assessment was also done for the present and the future for global model outputs for FCs in surface water and arsenic in groundwater, among other constituents. This assessment showed that for a business as usual scenario exceedance of FC limits for bathing water sharply increase in the poorest countries, while for arsenic in groundwater changes are limited (Bouwman *et al* 2024). Opportunities exist to expand such analyses to other constituents, although we should realise that the thresholds or standards are debated in the literature (Damania *et al* 2019) and need to have sufficient safety margins incorporated.

While the individual health risk assessments provide important quantitative input that helps us to understand the impact of water quality on human health, in reality people are exposed to multiple constituents at the same time and potential increased susceptibility to a disease can be expected when the body is already weakened by exposure to another contaminant (Genthe *et al* 2013). Therefore, ideally a cumulative risk assessment for water quality is performed (Koppe *et al* 2006, Genthe *et al* 2013). This cumulative risk assessment could include the different constituents and exposure pathways. The result of this assessment will provide a strong message to decision makers, demonstrating the importance of water quality for public health and advocating regulation and policy.

6. Lessons learned and way forward

In this paper, we have listed several water quality constituents that affect human health and their impacts. The diverse range of constituents relevant for human health, and the wide variety in potential health impacts demonstrates that this topic demands attention. The availability of *in situ* data for the relevant water quality constituents is limited, in particular in several regions across the world (e.g. Africa, parts of Asia) and for groundwater. Remote sensing techniques are promising and already operationally used for water quality monitoring, but can only focus on visible contamination in surface waters, or indirectly provide proxies of other (non-optical) constituents such as nutrient concentrations, while being limited by cloud cover and presence of lake ice cover in winter months in high latitudes and at high altitudes. Large-scale water quality models provide opportunities for future scenario analysis and are available for several, but certainly not all water quality constituents. Current model results cannot easily be compared and harmonisation of input data and consistency of model scale and resolution are required to provide outputs for a range of comparable water quality constituents. Integrated *in situ*, remote sensing and model data provide a more comprehensive assessment of water quality, although data gaps are still apparent. Also health data availability remains limited. Most available data represent the past and the present. Future data, required to understand potential changes in water quality relevant for human health, have only just started to emerge for the large scale. These currently focus mostly on long-term trends and are not yet able to capture the impacts of future projected climate extremes, such as floods and droughts, which are expected to severely affect the water quality and, thus, influence the exposure of populations to contaminated water. Where water quality data are available, despite the gaps and uncertainties, the link with human health impacts is not often made. However, approaches exist to determine the health risk related to exposure to contaminated water.

To obtain a much more comprehensive understanding of present and future water quality and consequent human health impacts, and to improve water quality to support SDG6 (clean water) and SDG3 (health), there is a need for an integrated, solution-oriented approach. This integrated approach should incorporate multiple constituents, as many constituents have a range of direct and indirect human health impacts. The approach should study mixed impacts on health, as a cocktail of constituents may have synergistic harmful impacts on human health. The approach should also be solution-oriented and focus on interventions that can improve human health. Ideally, human health is studied in relation to other impacts of water quality, such as impacts on aquatic ecosystems and food production. Synergies and trade-offs between the constituents, human health, other impacts of water quality, such as on animal health, ecosystem health (taking a one health approach) or food security, and interventions should be studied and incorporated. In the approach, uncertainty analysis should be incorporated to enhance credibility. And finally, the socio-economic, legal and policy dimensions of this complex problem, that have not been the focus of this paper, should be incorporated in the integrated and solution oriented approach.

That water quality deterioration is a strong concern for human health now and in the future is clear. Our study calls for a comprehensive and solution-oriented assessment. However, until such an assessment becomes part of policy and research agendas, several of no-regret interventions have been suggested and should be continued to be implemented. Improving water quality for many constituents will positively affect human health.

Acknowledgments

The authors do not have any conflicts of interest.

Data availability statement

The data for figure 1 is more extensively presented in Jones *et al* (2024b), and are available upon request from the corresponding author.

The data and R script for figure 2 from the GloWPa, Dynqual and Worldqual models are available upon request from the corresponding author.

Author contributions

Nynke Hofstra 0000-0002-0409-5145
Conceptualization (lead), Formal analysis (lead), Investigation (lead), Methodology (lead), Visualization (lead), Writing – original draft (lead), Writing – review & editing (lead)

Martina Flörke 0000-0003-2943-5289
Conceptualization (equal), Writing – original draft (equal), Writing – review & editing (equal)

Edward Jones 0000-0001-5388-7774
Conceptualization (equal), Formal analysis (equal), Writing – original draft (equal), Writing – review & editing (equal)

Issoufou Ouedraogo
Writing – original draft (equal), Writing – review & editing (equal)

Joel Podgorski
Writing – original draft (equal), Writing – review & editing (equal)

Eirini Politi 0000-0002-4005-8608
Conceptualization (equal), Writing – original draft (equal), Writing – review & editing (equal)

Katrin Schweden
Writing – original draft (equal), Writing – review & editing (equal)

Stefan Simis
Conceptualization (equal), Writing – original draft (equal), Writing – review & editing (equal)

Kerstin Stelzer
Writing – original draft (equal), Writing – review & editing (equal)

Maryna Strokal 0000-0002-8063-7743
Conceptualization (equal), Writing – original draft (equal), Writing – review & editing (equal)

Michelle T H van Vliet 0000-0002-2597-8422
Writing – original draft (equal), Writing – review & editing (equal)

Stijn Peeters 0000-0003-1354-8334
Conceptualization (equal), Visualization (equal), Writing – original draft (equal), Writing – review & editing (equal)

Appendix. Large-scale water quality models

Table A1. Summary of the large-scale models that are included in section 3.3 of this study. BOD, FC, TDS, and WT are short for biological oxygen demand, faecal coliforms, total dissolved solids, and water temperature, respectively. This table has been modified from. Reproduced from Strokal *et al* (2025). © The Author(s). Published by IOP Publishing Ltd. CC BY 4.0.

Name	Full name	Spatial details of model inputs and outputs		Temporal details of model inputs and outputs		Constituents	Details in:
		Resolution	Extent	Resolution	Extent		
DynQual	Dynamical surface water quality model	5 arcminutes grid cell	Global	Monthly	Up to 2100	FC, BOD, TDS, WT	(Jones *et al* 2023; Jones *et al* 2024a)
GloWPa	Global Waterborne Pathogen Model	0.5° grid cell	Global	Monthly	Up to 2100	*Cryptosporidium*	(Vermeulen *et al* 2019)
GREEN	Geospatial Regression Equation for European Nutrient losses	Sub-basin	Europe	Annual	Up to 2050	Nutrients	(Grizzetti *et al* 2008; Vigiak *et al* 2023)
IMAGE-GNM	IMAGE-Global Nutrient Model	0.5° grid cell	Global	Annual	Up to 2050	Nutrients	(Beusen *et al* 2022)
MARINA	Model to Assess River Inputs of pollutaNts to seAs	Sub-basin	Global	Annual	Up to 2100	Nutrients, plastics, chemicals	(Micella *et al* 2024; Ural-Janssen *et al* 2024)
mQM	multiscale Water Quality Model	0.5° grid cell	Europe	Annual	Up to 2050	Nutrients	(Kumar *et al* 2020; Nguyen *et al* 2022)
SWAT+	Soil and Water Assessment Tool	Hydrological response units	Africa	Monthly	Varied	Nutrients	(Akoko *et al* 2021; Chawanda *et al* 2025; Nkwasa *et al* 2024, Nkwasa *et al* 2025)
WorldQual	—	5 arcminutes grid cell	Global	Monthly	Up to 2100	Nutrients, FC, BOD, TDS, and WT	(Fink *et al* 2018; Reder *et al* 2015; Voß *et al* 2012)

References

Akoko G, Le T H, Gomi T and Kato T 2021 A review of SWAT model application in Africa *Water* **13** 1313

Ali M, Lopez A L, You Y A, Kim Y E, Sah B, Maskery B and Clemens J 2012 The global burden of cholera *Bull. World Health Organ.* **90** 209–18

Amaral-Zettler L A, Zettler E R, Mincer T J, Klaassen M A and Gallager S M 2021 Biofouling impacts on polyethylene density and sinking in coastal waters: a macro/micro tipping point? *Water Res.* **201** 117289

Amini M, Mueller K, Abbaspour K C, Rosenberg T, Afyuni M, Møller K N, Sarr M and Johnson C A 2008 Statistical modeling of global geogenic fluoride contamination in groundwaters *Environ. Sci. Technol.* **42** 3662–8

Anas A *et al* 2021 Dynamics of vibrio cholerae in a typical tropical lake and estuarine system: potential of remote sensing for risk mapping *Remote Sens.* **13** 1034

Aus der Beek T, Weber F A, Bergmann A, Hickmann S, Ebert I, Hein A and Küster A 2016 Pharmaceuticals in the environment-Global occurrences and perspectives *Environ. Toxicol. Chem.* **35** 823–35

Aw T 2018 Environmental aspects and features of critical pathogen groups *Global Water Pathogen Project* ed J B Rose and B Jimenez-Cisneros (UNESCO) (https://doi.org/10.14321/waterpathogens.2)

Ayoob S and Gupta A K 2006 Fluoride in drinking water: a review on the status and stress effects *Crit. Rev. Environ. Sci. Technol.* **36** 433–87

Backer L C, Manassaram-Baptiste D, LePrell R and Bolton B 2015 Cyanobacteria and algae blooms: review of health and environmental data from the harmful algal bloom-related illness surveillance system (HABISS) 2007–2011 *Toxins* **7** 1048–64

Barboza L G A, Dick Vethaak A, Lavorante B R B O, Lundebye A K and Guilhermino L 2018 Marine microplastic debris: an emerging issue for food security, food safety and human health *Mar. Pollut. Bull.* **133** 336–48

Basu N B *et al* 2022 Managing nitrogen legacies to accelerate water quality improvement *Nat. Geosci.* **15** 97–105

Ben Y, Fu C, Hu M, Liu L, Wong M H and Zheng C 2019 Human health risk assessment of antibiotic resistance associated with antibiotic residues in the environment: a review *Environ. Res.* **169** 483–93

Beusen A H W, Doelman J C, Van Beek L P H, Van Puijenbroek P J T M, Mogollón J M, Van Grinsven H J M, Stehfest E, Van Vuuren D P and Bouwman A F 2022 Exploring river nitrogen and phosphorus loading and export to global coastal waters in the shared socio-economic pathways *Glob. Environ. Change* **72** 102426

Boelee E, Geerling G, van der Zaan B, Blauw A and Vethaak A D 2019 Water and health: from environmental pressures to integrated responses *Acta Tropica* 193 217–26

Bouwman A F *et al* 2024 Multimodel and multiconstituent scenario construction for future water quality *Environ. Sci. Technol. Lett.* **11** 1272–80

Bradl H B 2005 Chapter 1 sources and origins of heavy metals *Interface Sci. Technol.* **6** 1–27

Caller T A, Doolin J W, Haney J F, Murby A J, West K G, Farrar H E, Ball A, Harris B T and Stommel E W 2009 A cluster of amyotrophic lateral sclerosis in New Hampshire: a possible role for toxic cyanobacteria blooms *Amyotrophic Lateral Sclerosis* **10** 101–8

Canter L W 1996 *Nitrates in Groundwater* (Lewis Publishers)

Caretta M A *et al* 2022 Water *Climate Change 2022—Impacts, Adaptation and Vulnerability* ed H-O Pörtner (Cambridge University Press) pp 551–712

Carrea L *et al* 2022 *ESA Lakes Climate Change Initiative (Lakes_cci): Lake Products, Version 2.0* (NERC EDS Centre for Environmental Data Analysis) (https://doi.org/10.5285/AB8D21568C81491FBB9A300C36884AF7)

Chawanda C J, van Griensven A, Nkwasa A, Teran Orsini J P, Jeong J, Choi S-K, Srinivasan R and Arnold J G 2025 A high-resolution global SWAT+ hydrological model for impact studies *EGUsphere* **2025** 1–27

Chowdhury S, Mazumder M A J, Al-Attas O and Husain T 2016 Heavy metals in drinking water: occurrences, implications, and future needs in developing countries *Sci. Total Environ.* **569** 476–88

Choy R K M and Huston C D 2020 Cryptosporidiosis should be designated as a tropical disease by the US food and drug administration *PLoS Negl. Trop. Dis.* **14** 1–6

Clerc S, Pflug B, Rivoire L, Pertiwi A P, Enache S, Lannone R Q, Celesti M, Camarero R, Reina F and Mavrocordatos C 2024 Impact of varying SNR in L1C data on Sentinel-2 L2A products *Proc. SPIE* **13192** 269–75

Codd G, Bell S, Kaya K, Ward C, Beattie K and Metcalf J 1999 Cyanobacterial toxins, exposure routes and human health *Eur. J. Phycol.* **34** 405–15

Copernicus Land Monitoring Service, & Copernicus Land Monitoring Service Helpdesk 2024a Lake Water Quality 2024-present (raster 300 m), global, 10-daily—version 2 (Copernicus Land Monitoring Service) (https://doi.org/10.2909/801137B8-9575-43EF-A073-140B663CC61C)

Copernicus Land Monitoring Service, & Copernicus Land Monitoring Service Helpdesk 2024b Lake water quality (raster 100 m), global, 10-daily—version 2 (Copernicus Land Monitoring Service) (https://doi.org/10.2909/DEAE3DB1-A214-4375-8D1A-63C42498050E)

Dai M *et al* 2023 Persistent eutrophication and hypoxia in the coastal ocean *Camb. Prisms: Coast. Futures* **1** e19

Damania R, Desbureaux S, Rodella A-S, Russ J and Zaveri E 2019 Quality unknown

de Jesus Gaffney V, Almeida C M M, Rodrigues A, Ferreira E, Benoliel M J and Cardoso V V 2015 Occurrence of pharmaceuticals in a water supply system and related human health risk assessment *Water Res.* **72** 199–208

Desbureaux S, Mortier F, Zaveri E, van Vliet M T H, Russ J, Rodella A S and Damania R 2022 Mapping global hotspots and trends of water quality (1992–2010): a data driven approach *Environ. Res. Lett.* **17** 114048

Dhillon A and Rowlins P E 2025 Climate change, harmful algal blooms, and cutaneous disease *JAAD Rev.* **4** 156–66

Doelman J C *et al* 2018 Exploring SSP land-use dynamics using the IMAGE model: regional and gridded scenarios of land-use change and land-based climate change mitigation *Glob. Environ. Change* **48** 119–35

Epstein P R 1993 Algal blooms in the spread and persistence of cholera *Biosystems* **31** 209–21

Fenton S E, Ducatman A, Boobis A, DeWitt J C, Lau C, Ng C, Smith J S and Roberts S M 2021 Per- and polyfluoroalkyl substance toxicity and human health review: current state of knowledge and strategies for informing future research *Environ. Toxicol. Chem.* **40** 606–30

Fink G, Alcamo J, Flörke M and Reder K 2018 Phosphorus loadings to the world's largest lakes: sources and trends *Glob. Biogeochem. Cycles* **32** 617–34

Frieler K *et al* 2017 Assessing the impacts of 1.5â€°C global warming—simulation protocol of the inter-sectoral impact model intercomparison project (ISIMIP2b) *Geosci. Model Dev.* **10** 4321–45

Frincu R M 2025 Artificial intelligence in water quality monitoring: a review of water quality assessment applications *Water Qual. Res. J.* **60** 164–76
Fuller R *et al* 2022 Pollution and health: a progress update *Lancet Planet. Health* **6** e535–e547
Gander M J 2025 Climate change and the water quality threats posed by the emerging contaminants per- and polyfluoroalkyl substances (PFAS) and microplastics *Water Int.* **50** 306–28
Genthe B, Le Roux W J, Schachtschneider K, Oberholster P J, Aneck-Hahn N H and Chamier J 2013 Health risk implications from simultaneous exposure to multiple environmental contaminants *Ecotoxicol. Environ. Saf.* **93** 171–9
Gleick P H 2014 The world's water *The World's Water* **8** 1–476
Grattan L M, Holobaugh S and Morris J G 2016 Harmful algal blooms and public health *Harmful Algae* **57** 2–8
Grizzetti B, Bouraoui F and De Marsily G 2008 Assessing nitrogen pressures on European surface water *Glob. Biogeochem. Cycles* **22** GB4023
He S *et al* 2022 Biofilm on microplastics in aqueous environment: physicochemical properties and environmental implications *J. Hazard. Mater.* **424** 127286
Hughes M F 2002 Arsenic toxicity and potential mechanisms of action *Toxicol. Lett.* **133** 1–16
Huisman J, Codd G A, Paerl H W, Ibelings B W, Verspagen J M H and Visser P M 2018 Cyanobacterial blooms *Nat. Rev. Microbiol.* **16** 471–83
Ijomone O M, Ifenatuoha C W, Aluko O M, Ijomone O K and Aschner M 2020 The aging brain: impact of heavy metal neurotoxicity *Crit. Rev. Toxicol.* **50** 801–14
International Programme on Chemical Safety 2002 *Fluorides* (World Health Organization) p 268 (available at: https://apps.who.int/iris/handle/10665/42415)
Ippolito A and Fait G 2019 Pesticides in surface waters: from edge-of-field to global modelling *Curr. Opin. Environ. Sustain.* **36** 78–84
Jones E R 2024 Global water quality monitoring dataset (https://doi.org/10.6084/m9.figshare.25965394.v1)
Jones E R *et al* 2025 A multi-model assessment of global freshwater temperature and thermoelectric power supply under climate change *Environ. Res. Water* **1** 025002
Jones E R, Bierkens M F P and van Vliet M T H 2024a Current and future global water scarcity intensifies when accounting for surface water quality *Nat. Clim. Change* **14** 629–35
Jones E R, Bierkens M F P, Wanders N, Sutanudjaja E H, Van Beek L P H and Van Vliet M T H 2023 DynQual v1.0: a high-resolution global surface water quality model *Geosci. Model Dev.* **16** 4481–500
Jones E R, Graham D J, van Griensven A, Flörke M and van Vliet M T H 2024b Blind spots in global water quality monitoring *Environ. Res. Lett.* **19** 091001
Jorge D S F *et al* 2017 SNR (signal-to-noise ratio) impact on water constituent retrieval from simulated images of optically complex amazon lakes *Remote Sens.* **9** 644
Khalid N, Aqeel M, Noman A and Fatima Rizvi Z 2023 Impact of plastic mulching as a major source of microplastics in agroecosystems *J. Hazard. Mater.* **445** 130455
Khan J R, Awan N, Archie R J, Sultana N and Muurlink O 2020 The association between drinking water salinity and hypertension in coastal Bangladesh *Glob. Health J.* **4** 153–8
King K, Bramucci A R, Labbate M, Raina J B and Seymour J R 2022 Heterogeneous growth enhancement of vibrio cholerae in the presence of different phytoplankton species *Appl. Environ. Microbiol.* **88** e01158–22
Kiulia N M, Hofstra N, Vermeulen L C, Obara M A, Medema G and Rose J B 2015 Global occurrence and emission of rotaviruses to surface waters *Pathogens* **4** 229–55
Koelmans A A, Bakir A, Burton G A and Janssen C R 2016 Microplastic as a vector for chemicals in the aquatic environment: critical review and model-supported reinterpretation of empirical studies *Environ. Sci. Technol.* **50** 3315–26
Koelmans A A, Mohamed Nor N H, Hermsen E, Kooi M, Mintenig S M and De France J 2019 Microplastics in freshwaters and drinking water: critical review and assessment of data quality *Water Res.* **155** 410–22
Kooi M, Van Nes E H, Scheffer M and Koelmans A A 2017 Ups and downs in the ocean: effects of biofouling on vertical transport of microplastics *Environ. Sci. Technol.* **51** 7963–71
Koppe J G *et al* 2006 Exposure to multiple environmental agents and their effect *Acta Paediatr. Int. J. Paediatr.* **95** 106–13
Kumar R *et al* 2020 Strong hydroclimatic controls on vulnerability to subsurface nitrate contamination across Europe *Nat. Commun.* **11** 6302
Kumar V *et al* 2019 Global evaluation of heavy metal content in surface water bodies: a meta-analysis using heavy metal pollution indices and multivariate statistical analyses *Chemosphere* **236** 124364
Kyu H H *et al* 2025 Global, regional, and national age-sex-specific burden of diarrhoeal diseases, their risk factors, and aetiologies, 1990–2021, for 204 countries and territories: a systematic analysis for the global burden of disease study 2021 *Lancet Infect. Dis.* **25** 519–36
Landrigan P J *et al* 2018 The lancet commission on pollution and health *Lancet* **391** 462–512
Lange S, Mengel M, Treu S and Büchner M 2022 ISIMIP3a atmospheric climate input data (No Title) (ISIMIP Repository) (https://doi.org/10.48364/ISIMIP.982724.2)
Larsson D G J *et al* 2018 Critical knowledge gaps and research needs related to the environmental dimensions of antibiotic resistance *Environ. Int.* **117** 132–8
Lee D, Gibson J M D, Brown J, Habtewold J and Murphy H M 2023 Burden of disease from contaminated drinking water in countries with high access to safely managed water: a systematic review *Water Res.* **242** 120244
Li C, Busquets R and Campos L C 2020 Assessment of microplastics in freshwater systems: a review *Sci. Total Environ.* **707** 135578
Liao Y and Naghizadeh P 2023 Social bias meets data bias: the impacts of labeling and measurement errors on fairness criteria *Proc. AAAI Conf. Artificial Intelligence* vol 37 pp 8764–72
Limaheluw J, Medema G and Hofstra N 2019 An exploration of the disease burden due to Cryptosporidium in consumed surface water for sub-Saharan Africa *Int. J. Hyg. Environ. Health* **222** 856–63
Lin L, Yang H and Xu X 2022 Effects of water pollution on human health and disease heterogeneity: a review *Front. Environ. Sci.* **10** 880246
Linares A, Li X, Satterwhite L, Sun Y and Bedlack R 2024 A retrospective analysis of ALS clusters near algae blooms in North Carolina (P5-11.019) *Neurology* **102** 3353
Liu Z, Liao L, Yang H, Chen Z and Ji H 2024 Impact of micro-nano plastics on microorganisms and thus drinking water treatment effectiveness: a review *Desalin. Water Treat.* **320** 100673

Ma Y, Egodawatta P, McGree J, Liu A and Goonetilleke A 2016 Human health risk assessment of heavy metals in urban stormwater *Sci. Total Environ.* **557** 764–72

Machiwal D, Cloutier V, Güler C and Kazakis N 2018 A review of GIS-integrated statistical techniques for groundwater quality evaluation and protection *Environ. Earth Sci.* **77** 1–30

Matthews M W, Bernard S and Robertson L 2012 An algorithm for detecting trophic status (chlorophyll-a), cyanobacterial-dominance, surface scums and floating vegetation in inland and coastal waters *Remote Sens. Environ.* **124** 637–52

Matthews M W and Odermatt D 2015 Improved algorithm for routine monitoring of cyanobacteria and eutrophication in inland and near-coastal waters *Remote Sens. Environ.* **156** 374–82

Metcalf J S and Codd G A 2009 Cyanobacteria, neurotoxins and water resources: are there implications for human neurodegenerative disease? *Amyotrophic Lateral Sclerosis* **10** 74–78

Micella I, Kroeze C, Bak M P, Tang T, Wada Y and Strokal M 2024 Future scenarios for river exports of multiple pollutants by sources and sub-basins worldwide: rising pollution for the Indian Ocean *Earth's Future* **12** e2024EF004712

Mishra A, Kumari M, Kumar R, Iqbal K and Thakur I S 2022 Persistent organic pollutants in the environment: risk assessment, hazards, and mitigation strategies *Bioresour. Technol. Rep.* **19** 101143

Momba M and Azab El-Liethy M 2017 Vibrio cholerae and Cholera biotypes *Global Water Pathogen Project* eds J B Rose and B Jiménez-Cisneros (UNESCO) (https://doi.org/10.14321/waterpathogens.28)

Morais S, Garcia E Costa F and de Lourdes Pereira M 2012 Heavy metals and human health *Environmental Health—Emerging Issues and Practice* ed J Oosthuizen (InTech) pp 227–46 (available at: https://books.google.com/books/about/Environmental_Health.html?id=vDqZDwAAQBAJ)

Murray C J *et al* 2022 Global burden of bacterial antimicrobial resistance in 2019: a systematic analysis *Lancet* **399** 629–55

Naghavi M *et al* 2024 Global burden of bacterial antimicrobial resistance 1990–2021: a systematic analysis with forecasts to 2050 *Lancet* **404** 1199–226

National Research Council (U.S.). Committee on Indicators for Waterborne Pathogens 2004 *Indicators for Waterborne Pathogens. National Academies Press* (for waterborne pathogens national academies press) (available at: https://books.google.com/books?hl=en&lr=&id=98SbAgAAQBAJ&oi=fnd&pg=PT13&dq=indicators+for+waterborne+pathogens+national+academies+press&ots=4Q5USv_GQ-&sig=5eQDGY-weqHCMHJVkL7p1sxQ6bM#v=onepage&q=indicators)

Nguyen T V, Sarrazin F J, Ebeling P, Musolff A, Fleckenstein J H and Kumar R 2022 Toward understanding of long-term nitrogen transport and retention dynamics across german catchments *Geophys. Res. Lett.* **49** e2022GL100278

Nkwasa A, James Chawanda C, Theresa Nakkazi M, Tang T, Eisenreich S J, Warner S and van Griensven A 2024 One third of African rivers fail to meet the'good ambient water quality' nutrient targets *Ecol. Indic.* **166** 112544

Nkwasa A, James Chawanda C, Theresa Nakkazi M and van Griensven A 2025 CoSWAT-WQ v1.0: a high-resolution community global SWAT+ water quality model *EGUsphere* **2025** 1–19

O'Neill B C, Kriegler E, Riahi K, Ebi K L, Hallegatte S, Carter T R, Mathur R and van Vuuren D P 2014 A new scenario framework for climate change research: the concept of shared socioeconomic pathways *Clim. Change* **122** 387–400

Ouedraogo I and Vanclooster M 2016 A meta-analysis and statistical modelling of nitrates in groundwater at the African scale *Hydrol. Earth Syst. Sci.* **20** 2353–81

Papathanasopoulou E *et al* 2019 Satellite-assisted monitoring of water quality to support the implementation of the water framework directive (https://doi.org/10.5281/ZENODO.3463051)

Paulino R S, Martins V S, Novo E M L M, Barbosa C C F, de Carvalho L A S and Begliomini F N 2022 Assessment of adjacency correction over inland waters using Sentinel-2 MSI images *Remote Sens.* **14** 1829

Pinto A, Botelho M J, Churro C, Asselman J, Pereira P and Pereira J L 2023 A review on aquatic toxins—do we really know it all regarding the environmental risk posed by phytoplankton neurotoxins? *J. Environ. Manage.* **345** 118769

Podgorski J and Berg M 2020 Global threat of arsenic in groundwater *Science* **368** 845–50

Podgorski J and Berg M 2022 Global analysis and prediction of fluoride in groundwater *Nat. Commun.* **13** 1–9

Poikane S *et al* 2015 A hitchhiker's guide to European lake ecological assessment and intercalibration *Ecol. Indic.* **52** 533–44

Politi E and Prairie Y T 2018 The potential of earth observation in modelling nutrient loading and water quality in lakes of southern Québec, Canada *Aquat. Sci.* **80** 1–16

Prata J C, da Costa J P, Lopes I, Duarte A C and Rocha-Santos T 2020 Environmental exposure to microplastics: an overview on possible human health effects *Sci. Total Environ.* **702** 134455

Prüss-Ustün A, Wolf J, Bartram J, Clasen T, Cumming O, Freeman M C, Gordon B, Hunter P R, Medlicott K and Johnston R 2019 Burden of disease from inadequate water, sanitation and hygiene for selected adverse health outcomes: an updated analysis with a focus on low- and middle-income countries *Int. J. Hyg. Environ. Health* **222** 765–77

Racault M F *et al* 2019 Environmental reservoirs of vibrio cholerae: challenges and opportunities for ocean-color remote sensing *Remote Sens.* **11** 2763

Rahman M M, Ng J C and Naidu R 2009 Chronic exposure of arsenic via drinking water and its adverse health impacts on humans *Environ. Geochem. Health* **31** 189–200

Reder K, Alcamo J and Flörke M 2017 A sensitivity and uncertainty analysis of a continental-scale water quality model of pathogen pollution in African rivers *Ecol. Modelling* **351** 129–39

Reder K, Flörke M and Alcamo J 2015 Modeling historical fecal coliform loadings to large European rivers and resulting in-stream concentrations *Environ. Modelling Softw.* **63** 251–63

Reinl K L *et al* 2023 Blooms also like it cold *Limnol. Oceanogr. Lett.* **8** 546–64

Rist S, Carney Almroth B, Hartmann N B and Karlsson T M 2018 A critical perspective on early communications concerning human health aspects of microplastics *Sci. Total Environ.* **626** 720–6

Rittel H W J and Webber M M 1973 Dilemmas in a general theory of planning *Policy Sci.* **4** 155–69

Rytkönen A, Meriläinen P, Valkama K, Hokajärvi A M, Ruponen J, Nummela J, Mattila H, Tulonen T, Kivistö R and Pitkänen T 2024 Scenario-based assessment of fecal pathogen sources affecting bathing water quality: novel treatment options to reduce norovirus and Campylobacter infection risks *Front. Microbiol.* **15** 1353798

Sambaza S S and Naicker N 2023 Contribution of wastewater to antimicrobial resistance: a review article *J. Glob. Antimicrob. Resist.* **34** 23–29

Santer R and Schmechtig C 2000 Adjacency effects on water surfaces: primary scattering approximation and sensitivity study *Appl. Opt.* **39** 361–75

Schaeffer B A, Urquhart E, Coffer M, Salls W, Stumpf R P, Loftin K A and Jeremy Werdell P 2022 Satellites quantify the spatial extent of cyanobacterial blooms across the United States at multiple scales *Ecol. Indic.* **140** 108990
Schmidt C *et al* 2023 Quality known contents
Schwarzenbach R P, Egli T, Hofstetter T B, Von Gunten U and Wehrli B 2010 Global water pollution and human health *Annu. Rev. Environ. Resour.* **35** 109–36
Senathirajah K, Attwood S, Bhagwat G, Carbery M, Wilson S and Palanisami T 2021 Estimation of the mass of microplastics ingested—a pivotal first step towards human health risk assessment *J. Hazard. Mater.* **404** 124004
Sengupta D *et al* 2025 Sensing human health from space: an assessment of applications and big data platforms *Remote Sens. Appl.* **39** 101701
Shammi M, Rahman M, Bondad S and Bodrud-Doza M 2019 Impacts of salinity intrusion in community health: a review of experiences on drinking water sodium from coastal areas of bangladesh *Healthcare* **7** 50
Sharif-Askari E, Zeitoun-Ghandour S, Atoui K, Rizk M, Al Souki K S, Moravec J, Trögl J and Jaffal H G 2025 Lebanese rivers status: juggling between public negligence and challenged scientific awareness *Environ. Res. Lett.* **20** 063002
Strokal M *et al* 2019 Global multi-pollutant modelling of water quality: scientific challenges and future directions *Curr. Opin. Environ. Sustain.* **36** 116–25
Strokal M *et al* 2025 Advancing water quality model intercomparisons under global change: perspectives from the new ISIMIP water quality sector *Environ. Res. Water* **1** 035002
Strokal M, Kroeze C, Wang M, Bai Z and Ma L 2016 The MARINA model (model to assess river inputs of nutrients to seAs): model description and results for China *Sci. Total Environ.* **562** 869–88
Strokal M, Vriend P, Bak M P, Kroeze C, van Wijnen J and van Emmerik T 2023 River export of macro- and microplastics to seas by sources worldwide *Nat. Commun.* **14** 1–13
Strokal M, Wang M, Micella I and Janssen A B G 2024 Building trust in large-scale water quality models: 13 alternative strategies beyond validation *Discover Water* **4** 1–11
Su Y, Gao R, Huang F, Liang B, Guo J, Fan L, Wang A and Gao S-H 2024 Occurrence, transmission and risks assessment of pathogens in aquatic environments accessible to humans *J. Environ. Manage.* **354** 120331
Tapley B D, Reigber C, Tapley B D and Reigber C 2002 The grace mission: status and future plans *EGS General Assembly Conf. Abstracts* pp 4819 (available at: https://ui.adsabs.harvard.edu/abs/2002EGSGA.27.4819T/abstract)
Thorslund J and van Vliet M T H 2020 A global dataset of surface water and groundwater salinity measurements from 1980–2019 *Sci. Data* **7** 231
UNEP 2016 *A Snapshot of the World's Water Quality: Towards a Global Assessment* (available at: https://978-92-807-3555-0)
United Nations 2015 *Transforming our world: the 2030 Agenda for Sustainable Development* (available at: https://sdgs.un.org/2030agenda)
Ural-Janssen A, Kroeze C, Meers E and Strokal M 2024 Large reductions in nutrient losses needed to avoid future coastal eutrophication across Europe *Mar. Environ. Res.* **197** 106446
US EPA 1987 *The Risk Assessment Guidelines of 1986* (available at: https://books.google.nl/books?hl=nl&lr=&id=dMOFI5A_HLEC&oi=fnd&pg=PR4&dq=U.S.+Environmental+Protection+Agency,+1987.+Risk+Assessment+Guidelines+of+1986.&ots=LaaImetlZO&sig=1wTn0FPzRIiGBJwhc4dISl7Z_vI)
US EPA n.d. *What Are the Effects of HABs | US EPA* (available at: www.epa.gov/habs/what-are-effects-habs) (Accessed 25 June 2025)
Van Puijenbroek P J T M, Bouwman A F, Beusen A H W and Lucas P L 2015 Global implementation of two shared socioeconomic pathways for future sanitation and wastewater flows *Water Sci. Technol.* **71** 227–33
Van Puijenbroek P, Beusen A and Bouwman A 2023 Quantifying future sanitation scenarios and progress towards SDG targets in the shared socioeconomic pathways *J. Environ. Manage.* **346** 118921
Van Vliet M T H, Thorslund J, Strokal M, Hofstra N, Flörke M, Ehalt Macedo H, Nkwasa A, Tang T, Kaushal S S and Kumar R 2023 Global river water quality under climate change and hydroclimatic extremes *Nat. Rev. Earth Environ.* **4** 687–702
van Wijnen J, Ragas A M J and Kroeze C 2018 River export of triclosan from land to sea: a global modelling approach *Sci. Total Environ.* **621** 1280–8
van Wijnen J, Ragas A M J and Kroeze C 2019 Modelling global river export of microplastics to the marine environment: sources and future trends *Sci. Total Environ.* **673** 392–401
Vasseghian Y, Hosseinzadeh S, Khataee A and Dragoi E-N 2021 The concentration of persistent organic pollutants in water resources: a global systematic review, meta-analysis and probabilistic risk assessment *Sci. Total Environ.* **796** 149000
Vermeulen L C, van Hengel M, Kroeze C, Medema G, Spanier J E, van Vliet M T H and Hofstra N 2019 Cryptosporidium concentrations in rivers worldwide *Water Res.* **149** 202–14
Vethaak A D and Leslie H A 2016 Plastic debris is a human health issue *Environ. Sci. Technol.* **50** 6825–6
Vigiak O, Udías A, Grizzetti B, Zanni M, Aloe A, Weiss F, Hristov J, Bisselink B, de Roo A and Pistocchi A 2023 Recent regional changes in nutrient fluxes of European surface waters *Sci. Total Environ.* **858** 160063
Villarrubia-Gómez P, Carney Almroth B, Eriksen M, Ryberg M and Cornell S E 2024 Plastics pollution exacerbates the impacts of all planetary boundaries *One Earth* **7** 2119–38
Voß A, Alcamo J, Bärlund I, Voß F, Kynast E, Williams R and Malve O 2012 Continental scale modelling of in-stream river water quality: a report on methodology, test runs, and scenario application *Hydrol. Process.* **26** 2370–84
Wang J, Guo X and Xue J 2021 Biofilm-developed microplastics as vectors of pollutants in aquatic environments *Environ. Sci. Technol.* **55** 12780–90
Wang J, Liu X, Beusen A H W and Middelburg J J 2023 Surface-water nitrate exposure to world populations has expanded and intensified during 1970–2010 *Environ. Sci. Technol.* **57** 19395–406
Wang Y, Zhao D, Woolway R I, Yan H, Paerl H W, Zheng Y, Zheng C and Feng L 2025 Global elevation of algal bloom frequency in large lakes over the past two decades *Natl Sci. Rev.* **12** nwaf011
Ward M H, Jones R R, Brender J D, De Kok T M, Weyer P J, Nolan B T, Villanueva C M and Van Breda S G 2018 Drinking water nitrate and human health: an updated review *Int. J. Environ. Res. Public Health* **15** 1557
WHO 2012 Pharmaceuticals in drinking water (available at: https://www.who.int/publications/i/item/9789241502085)
WHO 2015 *Global Action Plan on Antimicrobial Resistance*
WHO 2021a *Guidelines on Recreational Water Quality: Volume 1 Coastal and Fresh Waters* (available at: www.who.int/publications/i/item/9789240031302)

WHO 2021b *WHO Human Health Risk Assessment Toolkit: Chemical Hazards* 2nd edn (World Health Organisation) (available at: https://books.google.nl/books?hl=nl&lr=&id=AMBqEAAAQBAJ&oi=fnd&pg=PR9&dq=WHO+human+health+risk+assessment+toolkit:+chemical+hazards&ots=yTCdIL1Wb4&sig=da3IXRlErBoBYx6Fs-H6fhSutvo)

WHO 2022 Fourth edition incorporating the first and second addenda guidelines for drinking-water quality (available at: https://iris.who.int/bitstream/handle/10665/352532/9789240045064-eng.pdf?sequence=1)

Wolf J *et al* 2023 Burden of disease attributable to unsafe drinking water, sanitation, and hygiene in domestic settings: a global analysis for selected adverse health outcomes *Lancet* **401** 2060–71

Wołowicz A and Munir H M S 2025 Emerging organic micropollutants as serious environmental problem: a comprehensive review *Sci. Total Environ.* **958** 177948

World Water Quality Alliance 2021 World water quality assessment: first global display of a water quality baseline. A consortium effort by the world water quality alliance—towards a full global assessment *Information Document Annex for display at the 5th Session of the United Nations Environment Assembly*

Wuijts S, Driessen P P J and Van Rijswick H F M W 2018 Towards more effective water quality governance: a review of social-economic, legal and ecological perspectives and their interactions *Sustainability* **10** 914

Zhang Q *et al* 2025 More inputs of antibiotics into groundwater but less into rivers as a result of manure management in China *Environ. Sci. Ecotechnol.* **23** 100513

Zhang Q, Li Y, Kroeze C, Xu W, Gai L, Vitsas M, Ma L, Zhang F and Strokal M 2024 A global assessment of glyphosate and AMPA inputs into rivers: over half of the pollutants are from corn and soybean production *Water Res.* **261** 121986