ENVIRONMENTAL RESEARCH
LETTERS

PURPOSE-LED PUBLISHING™

Part of the ENVIRONMENTAL RESEARCH SERIES

ACCEPTED MANUSCRIPT • OPEN ACCESS

Future river exports of nutrients, plastics and chemicals worldwide under climate-driven hydrological changes

To cite this article before publication: Mirjam P. Bak *et al* 2025 *Environ. Res. Lett.* in press https://doi.org/10.1088/1748-9326/adf860

Future river exports of nutrients, plastics, and chemicals worldwide under climate-driven hydrological changes

Mirjam P. Bak[1*], Ilaria Micella[1*], Edward R. Jones[2], Rohini Kumar[3], Albert Nkwasa[4,5], Ting Tang[6], Michelle T.H. van Vliet[2], Mengru Wang[1], Maryna Strokal[1]

[*] Equal first authorship

[1]Earth Systems and Global Change Group, Wageningen University & Research, Wageningen, The Netherlands

[2]Department of Physical Geography, Faculty of Geosciences, Utrecht University, Utrecht, The Netherlands

[3]Department Computational Hydrosystems, Helmholtz Centre for Environmental Research GmbH - UFZ, Leipzig, 04318, Germany [3]Computational

[4]Water Security Research Group, Biodiversity and Natural Resources Program, International Institute for Applied Systems Analysis (IIASA), Schlossplatz 1, A-2361 Laxenburg, Austria

[5]Department of Water and Climate, Vrije Universiteit Brussel (VUB), 1050 Brussel, Belgium

[6]Biological and Environmental Science and Engineering Division, King Abdullah University of Science and Technology, Thuwal, Kingdom of Saudi Arabia

Corresponding authors: Mirjam P. Bak (mirjam.bak@wur.nl) & Ilaria Micella (ilaria.micella@wur.nl)

Abstract

Future climate-driven hydrological changes may strongly affect river exports of multiple pollutants to coastal waters. In large-scale water quality models the effects are, however, associated with uncertainties that may differ in space and time but are hardly studied worldwide and for multiple pollutants simultaneously. Moreover, explicit ways to assess climate-driven uncertainties in large-scale multi-pollutant assessments are currently limited. Here, we aim to build trust in future river exports of nutrients (i.e. nitrogen and phosphorus), plastics (i.e. micro and macroplastics), and chemicals (i.e. diclofenac and triclosan) under climate-driven hydrological changes on the sub-basin scale worldwide. We used a soft-coupled global hydrological (VIC) and water quality (MARINA-Multi) model system, driven by five Global Climate Models (GCMs), to quantify river exports of selected pollutants to seas for 2010 and 2050 under an economy-driven and high global warming scenario. Subsequently, we developed and applied a new approach to build trust in projected future trends in coastal water pollution for the selected pollutants. Results reveal that in arid regions, such as the Middle East, East Asia, and Northern Africa, climate-driven uncertainties play a key role in future river exports of pollutants. For African sub-basins, high increases in river exports of pollutants are projected by 2050 under climate-driven hydrological uncertainty. Nevertheless, over 80% of the global sub-basin areas agree on the direction of change in future river exports of individual pollutants for at least three GCMs. Multi-pollutant agreements differ among seas: 53% of the area agrees on increasing river exports of six pollutants into the Indian Ocean by 2050, whereas 17% agrees on decreasing trends for the Mediterranean Sea. Our study indicated that even under climate-driven hydrological uncertainties, large-scale water quality models remain useful tools for future water quality assessments. Yet, awareness and transparency of modelling uncertainties are essential when utilising model outputs for well-informed actions.

Keywords: water quality, multiple pollutants, building trust, climate, uncertainty, hydrological changes

1. Introduction

Nutrients, plastics, and chemicals enter rivers and then are exported to coastal waters[1-4]. Rivers export these pollutants often from common sources such as agricultural runoff and sewage systems[2,5-8] impacting the aquatic environment. Nutrient pollution, for example, triggers harmful algal blooms[9,10], while plastics and chemicals disrupt ecosystems[11,12]. Today, many rivers and coastal waters are exposed to multi-pollutant issues[13-16]. In the future, water pollution is likely to increase due to socio-economic developments like urbanisation and population growth[15-18].

Climate change is expected to influence river exports of pollutants because of long-term changes in runoff, river discharge patterns[16 19,20], and water storage[21,22]. In large-scale water quality models, this may affect flows of pollutants as well as their retention in river systems[17,18]. In addition, climate change affects terrestrial pollutant sources and biogeochemical processes. For example, rising temperatures can alter nutrient cycling and pollutant emissions[23]. This study, however, focuses specifically on the effects of climate-driven hydrological changes on river exports of multiple pollutants. The meteorological forcings (e.g. air temperature, precipitation) from Global Climate Models (CGMs) are often used by Global Hydrological Models (GHMs) to project runoff and river discharges, which are further used as input to global water quality models. Large-scale water quality models such as MARINA-Multi (Model to Assess River Inputs of pollutaNts to seAs)[18], IMAGE-GNM (Integrated Model to Assess the Global Environment-Global Nutrient Model)[24], SWAT+ (Soil and Water Assessment Tool)[25], WorldQual[26], and DynQual (Dynamical Surface Water Quality model)[27] are the most suitable tools to study water pollution issues on regional to global scales. They account for hydrological flows driven by GCMs. Yet, many GCMs depend on climate forcings that differ largely in space and time[28,29], adding uncertainties to hydrological projections[30]. The effects of these uncertainties, particularly on river exports of nutrients, plastics, and chemicals, are hardly studied worldwide in a spatially explicit way (knowledge gap 1).

Building trust under uncertainties associated with climate-driven hydrological changes is important for water quality assessments. Yet, to date, there is no comprehensive assessment of the uncertainties associated with hydrological drivers in large-scale water quality models. Traditional evaluation methods such as model validation at the catchment scale, are inadequate for the complexities of large-scale, climate-driven models: e.g. large diversity in pollutants and limited observation data[31,32]. Hence, large-scale models need thorough evaluation to ensure accuracy and reliability, especially for policymaking and environmental management. Gleeson et al.[33] and Strokal et al.[32] emphasise the need for new evaluation methods that go beyond validation, especially for emerging pollutants lacking observations[31]. Strokal et al.[32] presented a building trust approach for large-scale water quality models (see SI B) with 13 strategies to evaluate model inputs, outputs, and structures via comparisons, sensitivity analysis, innovations, expert knowledge, and local models[32]. However, those strategies focus on individual models rather than propagating uncertainties through modelling chains for multiple pollutants. Hence, explicit ways to assess climate-driven hydrological uncertainties in global multi-pollutant assessments of coastal waters are limited in current building trust approaches (knowledge gap 2).

Our study aims to build trust in future river exports of nutrients (i.e. nitrogen and phosphorus), plastics (i.e. micro and macro), and chemicals (i.e. triclosan and diclofenac) under climate-driven hydrological changes on the sub-basin scale worldwide. We define coastal water pollution as river exports of pollutants to seas (in loads). We used a soft-coupled water quantity (Variable Infiltration Capacity model; VIC[34,35]) and water quality (MARINA-Multi[18]) model system, driven by five GCMs, to simulate river exports of six pollutants in 2010 and 2050. We followed an economic-driven and high global warming scenario: Shared Socioeconomic Pathway 5[36] and Representative Concentration Pathway 8.5[37] (SSP5-RCP8.5)[38]. Then, we developed and applied a new approach to build trust in projected trends in coastal water pollution across GCMs and pollutants. Focusing on multiple pollutants simultaneously is important for two main reasons. First, since pollutants may have different sources and pathways, they may respond differently to climate-driven hydrological uncertainties[39]. Second, real-world exposures are typically to multiple pollutants[17,18], highlighting the need to understand the robustness of multi-pollutant trends under climate-driven hydrological uncertainties. This could support the development of environmental policies that are resilient to climate-driven uncertainties. Our study contributes to the first global-scale water quality model intercomparison effort as proposed by the Water Quality (WQ) sector of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) which is an international collaborative effort that assesses climate change impacts. (https://www.isimip.org/).

2. Methodology

2.1 A soft-coupled model system

We used a soft-coupled water quantity (VIC) and water quality (MARINA-Multi) model system: i.e. outputs of VIC were used as inputs to MARINA-Multi. VIC provided hydrological data driven by five GCMs (Figure 1). The MARINA-Multi model aims to analyse trends and sources of water pollution. Hence, it simulates annual river exports of dissolved inorganic (DIN, DIP) and dissolved organic (DON, DOP) nitrogen (N) and phosphorus (P), micro- (MIP), and macroplastics (MAP), triclosan (TCS), and diclofenac (DCL). We combined inorganic and organic nutrients into total dissolved N and P: TDN and TDP. This is done by source for 8,890 sub-basins for 2010 and 2050 in three steps.

First, the model simulates inputs of pollutants to rivers from point and diffuse sources (kg/year). Point sources include sewage systems and direct discharges of animal manure (only for China in 2010) and untreated human waste. Diffuse sources are distinguished between anthropogenic and non-anthropogenic (natural). Anthropogenic sources include synthetic fertilisers, animal manure, atmospheric N deposition on agricultural areas, biological N_2 fixation by crops, leaching of organic matter, weathering of P-contained minerals from agricultural areas and mismanaged plastic waste. For natural sources, the model includes atmospheric N deposition on non-agricultural areas, biological N_2 fixation by natural vegetation, leaching of organic matter, and weathering of P-contained minerals from non-agricultural areas. Inputs of pollutants from land (diffuse sources) to rivers are corrected for the retention and losses in the soil. Second, the model simulates inputs of pollutants reaching the outlets of sub-basins (kg/year). These inputs are corrected for retention and losses during the export (e.g., river damming, water removals, denitrification). Third, the model simulates river exports of pollutants to the river mouths (coastal waters) (kg/year) while considering retention and losses.

For our model runs, we used socio-economic and climate drivers following the combined storylines of SSP5-RCP8.5. This economy-driven scenario assumes high emissions and moderate population growth, with continued reliance on fossil fuels and a reactive approach to environmental challenges. Input data related to socio-economic aspects like population, urbanisation, land use, human development, wastewater treatment, agriculture, and waste management were directly taken from Micella et al.[18] (see SI A). VIC provided five runs for drivers namely river discharges based on five GCMs (Figure 1 and SI A).

We selected five different GCMs following the Coupled Model Intercomparison Project 5 (CMIP5)[40] and ISIMIP2b[41] (https://www.isimip.org/): (1) MIROC-ESM-CHEM[42], (2) IPSL-CM5A-LR[43], (3) HadGEM2-ES[44], (4) NorESM1-M[45], and (5) GFDL-ESM2M[46]. This selection covered a variety of features: e.g. their components differ in their resolutions and interaction levels[29]. Each GCM was used by VIC (version 4.1.2[34,35]) to simulate annual natural river discharges under RCP8.5. VIC is a widely used process-based hydrological model[19,47-51] that provided data at the 0.5-degree grid scale. We averaged the data over 2005-2015 (for 2010) and 2045-2055 (for 2050) and processed it to the sub-basin scale for MARINA-Multi[5,15,18], separately for all five GCMs (Figure 1, see SI A for details). We chose VIC because of its earlier integration into the MARINA-Multi model[19,47-51] (SI A and SI C) and VIC solves both surface energy and water balances[34,35]. The GCM forcing data for VIC were downscaled and bias-corrected following the trend-preserving ISIMIP approach[41].

2.2 Building trust under climate-driven uncertainties

We developed a three-stage approach to build trust under climate-driven uncertainties. This approach complements the 13 alternative strategies as identified by Strokal et al.[32]. In Stage 1, we analysed the ensemble mean and coefficient of variation (CV) in river exports of pollutants from five GCMs for 2010 and 2050. The ensemble mean was calculated by averaging the annual river exports of each pollutant per unit sub-basin area (kg/km^2/yr or g/km^2/yr) over five GCMs. The CV, calculated as the ratio of the standard deviation to the mean, indicates the spread in projected river exports of each pollutant among the five GCMs by sub-basin.

In Stage 2, we evaluated inter-GCM agreement (Table 1) for changes in river exports of single pollutants, focusing solely on 2010 and 2050. Agreements are associated with trust in model projections for individual pollutants, whereas disagreement indicates higher climate-driven uncertainty in projections. We first calculated the percentage change in river exports of pollutants by sub-basin between 2010 and 2050 per GCM (SI, Figure H.1). Second, we set a 5% threshold for changes in river exports of pollutants to determine the direction of change per GCM: >5% indicates an increase in river export, <-5% indicates a decrease in river export, and changes between -5% and 5% are deemed inconclusive. Finally, we assessed the agreement across GCMs for individual pollutants by sub-basin using the agreement classes as defined in Table 1.

In Stage 3, building on the outcomes of Stage 2 we analysed the multi-pollutant agreement (Table 1) by sub-basin and by sea. Agreements are associated with strong multi-pollutant trends, whereas disagreements indicate uncertainty in multi-pollutant trends. We estimated the area share of multi-pollutant agreement classes for five large seas in the world: the Arctic Sea, Mediterranean Sea, Atlantic Ocean, Pacific Ocean, and Indian Ocean (SI, Figure E.1).

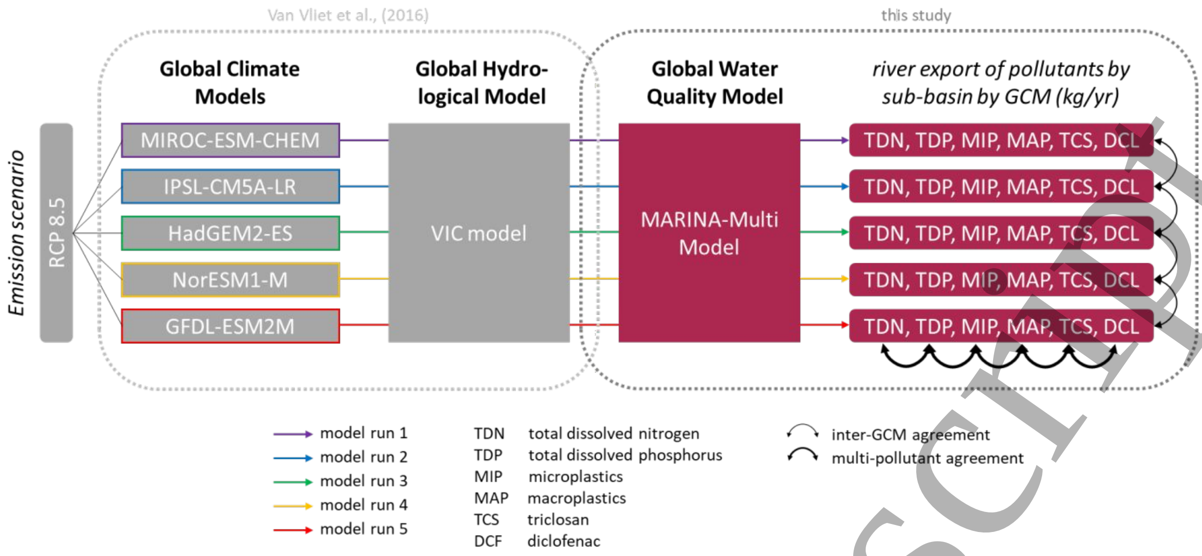


Figure 1: *Overview of the soft-coupled water quantity (light-grey dotted box) and water quality (dark-grey dotted box) model system. Global Climate Models (GCMs) provided inputs (forcings) to the hydrological VIC model that simulated river discharges for the water quality MARINA-Multi model. MARINA-Multi model outputs included river exports of nutrients (TDN, TDP), plastics (MIP, MAP) and chemicals (TCS, DCL) in loads (kg/yr). We used five GCMs resulting in five model runs. We used the results of the five model runs to analyse future inter-GCM and multi-pollutant agreements for sub-basins worldwide (see Table 1 for definitions). RCP8.5 is short for Representative Concentration Pathway 8.5. Source: see Section 2.2 for references to the GCMs and model descriptions.*

Table 1: *Agreement classes on the direction of change (increases or decreases) between the year 2010 and the year 2050 in river exports of pollutants to seas. The agreement classes are used to assess inter-GCM agreement for individual pollutants (Stage 2 in Section 2.2) and the multi-pollutant agreement for areas with moderate to very high inter-GCM agreements (Stage 3 in Section 2.2). Our study includes five GCMs and six pollutants at the sub-basin scale. GCM is short for Global Climate Model.*

Agreement classes	**Inter-GCM agreement** ***(number of GCMs agreeing on the direction of change for individual pollutants out of the 5 GCMs)***	**Multi-pollutant agreement** ***(number of pollutants agreeing on the direction of changes out of the 6 pollutants*)***
Very high	5/5	6/6
High	4/5	4-5/6
Moderate	3/5	3/6
Diverging	-	2/6 or 3/6 **
Disagreement	<3/5	≤ 2/6***

* Only applicable for areas with moderate to very high inter-GCM agreement.

** Equal agreement among pollutants. This applies to two situations: (A) 3 pollutants agree on an increasing trend, 3 pollutants agree on a decreasing trend; (B) 2 pollutants agree on an increasing trend, 2 pollutants agree on a decreasing trend, 2 pollutants show disagreements in trend (i.e. inter-GCM disagreement).

*** The majority of the pollutants disagree due to inter-GCM disagreements. Hence, the multi-pollutant agreement remains inconclusive. This applies to six situations: (A) 2 pollutants agree on an increasing trend, 1 pollutant shows a decreasing trend, 3 pollutants show disagreements in trends (i.e. inter-GCM disagreement); (B) 2 pollutants agree on a decreasing trend, 1 pollutant shows an increasing trend, 3 pollutants show disagreements in trends (i.e. inter-GCM disagreement); (C) 1 pollutant shows an increasing trend, 1 pollutant shows a decreasing trend, 4 pollutants show disagreements in trends (i.e. inter-GCM disagreement); (D) 1 pollutant shows an increasing trend, 5 pollutants show disagreements in trends (i.e. inter-GCM disagreement); (E) 1 pollutant shows an increasing trend, 5 pollutants show disagreements in trends (i.e. inter-GCM disagreement); (F) all 6 pollutants show disagreement in trends (i.e. inter-GCM agreement).

3. Results

3.1 Ensemble means and variability for individual pollutants (Stage 1)

Pollutant loads are projected to be high in many sub-basins of Asia, Europe, and Central America in 2050 (Figure 2). This holds for most pollutants: >900 kg/km^2/yr for TDN, >50 kg/km^2/yr for TDP, >1.5 kg/km^2/yr for MIP, >3 g/km^2/yr for TCS, and >0.9 g/km^2/yr for DCL. Exceptions are many sub-basins of Africa and Asia where rivers are projected to export more MAP (>6 kg/km^2/yr) compared to sub-basins elsewhere in the world. Generally, rivers are projected to export much TDN (50 Tg/yr globally) compared to other pollutants (e.g., 2.7 Tg/yr for TDP, 0.6 Tg/yr for MAP, and 0.2 Tg/yr for DCL globally).

Climate-driven uncertainties play a key role in water pollution in (highly) arid areas in 2050 (Figure 2). For example, the spread in river exports of all pollutants among the five GCMs (measured by CV) is generally large in the Middle Eastern, East Asian, South Asian, Northern African, and some North and Central American sub-basins (Figure 2). For those sub-basins, CVs are highest for nutrients (>0.45), but also relatively higher for plastics and chemicals (>0.05) compared to other regions. For nutrients, the spread is projected to be also large in Australian sub-basins. Conversely, the spread is generally small for all pollutants in sub-basins across (sub)arctic regions, Southeast Asia, and South America. Among pollutants, the spread is approximately four times larger for nutrients than for plastics and chemicals (Figure 2).

For Africa, mean river exports of pollutants are projected to increase largely under high climate-driven uncertainties. To illustrate, pollution levels in rivers are projected to rise under global change by 2050, ranging from 29-206% across pollutants. These increases in river exports of pollutants are often accompanied by a larger spread in future projections, suggesting the importance of climate-driven uncertainties in Africa: e.g., 48-60% of the sub-basin areas show higher CVs for pollutants in 2050 compared to 2010 (Figure 2 and SI G). Asian sub-basins show similar patterns, though less extreme, with pollution levels ranging from a 9% decrease to a 93% increase and higher CVs in 14-38% of the areas. Other regions displayed varying trends depending on the pollutant and projection (see SI G).

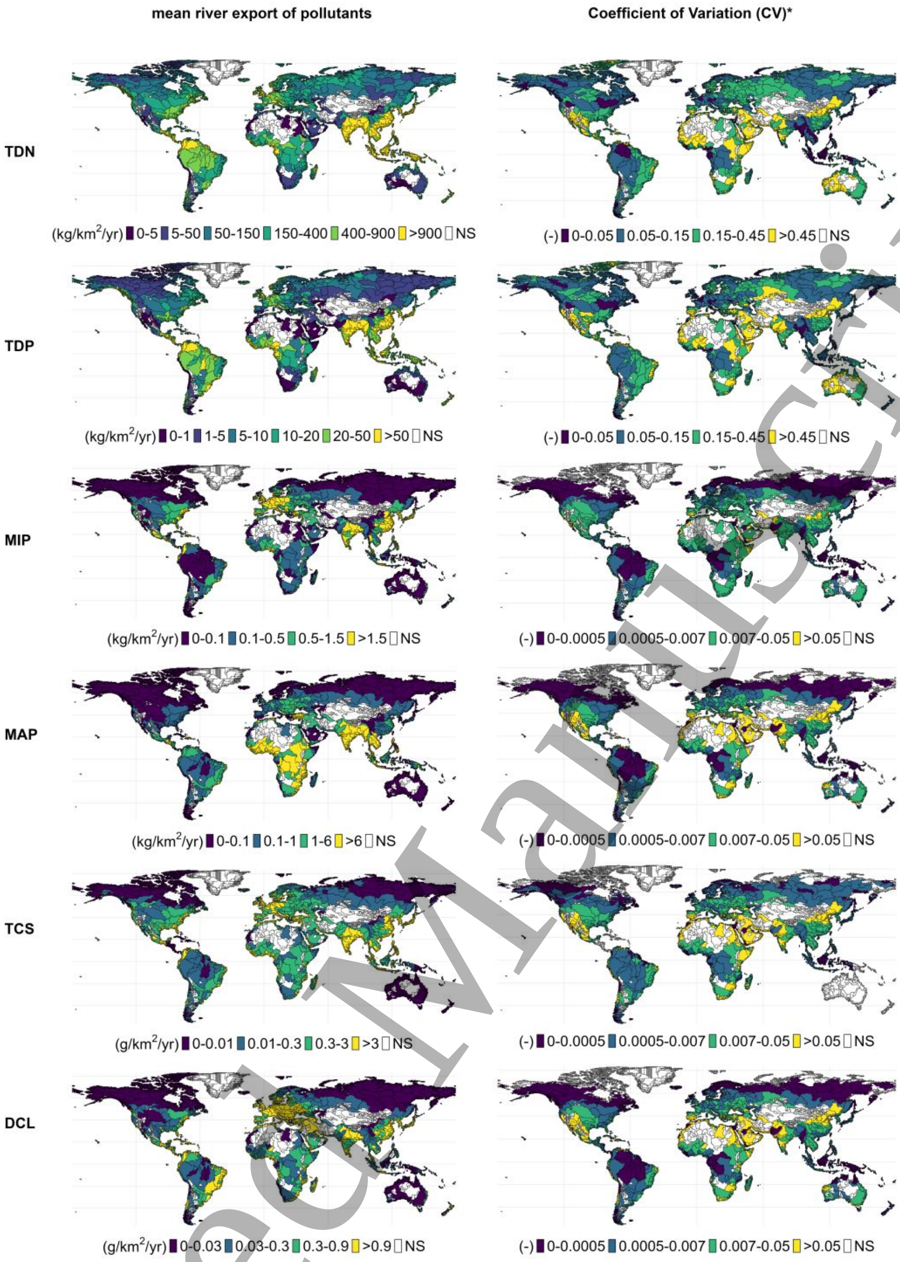


Figure 2: *Ensemble means of river exports of individual pollutants in loads at the sub-basin scale worldwide (left panels, kg/km²/yr or g/km²/yr) and their coefficient of variation associated with climate-induced hydrological changes (right panels, unitless) for the year 2050. The ensemble mean is estimated over five model runs, each of which is based on hydrology simulated using climate forcings from one of the five global climate models. CV is short for the coefficient of variation, which is the ratio of standard deviation to the mean. *=bins of CVs are different for nutrients (TDN, TDP) compared to plastics (MIP, MAP) and chemicals (TCS, DCL) to show spatial variability. Pollutants include total dissolved nitrogen (TDN), total dissolved phosphorus (TDP), microplastics (MIP), macroplastics (MAP), triclosan (TCS), and diclofenac (DCL). 2050 is based on Shared Socioeconomic Pathway 5 (rapid urbanisation and high economic development) and Representative Concentrative Pathway 8.5 (high global warming). NS (Not part of the Study area) denotes sub-basins that are not part of our study area as they do not drain into the seas or are part of Greenland (see SI, Figure E.1 for details). Source: the MARINA-Multi model (see Section 2 for the model and scenario descriptions).*

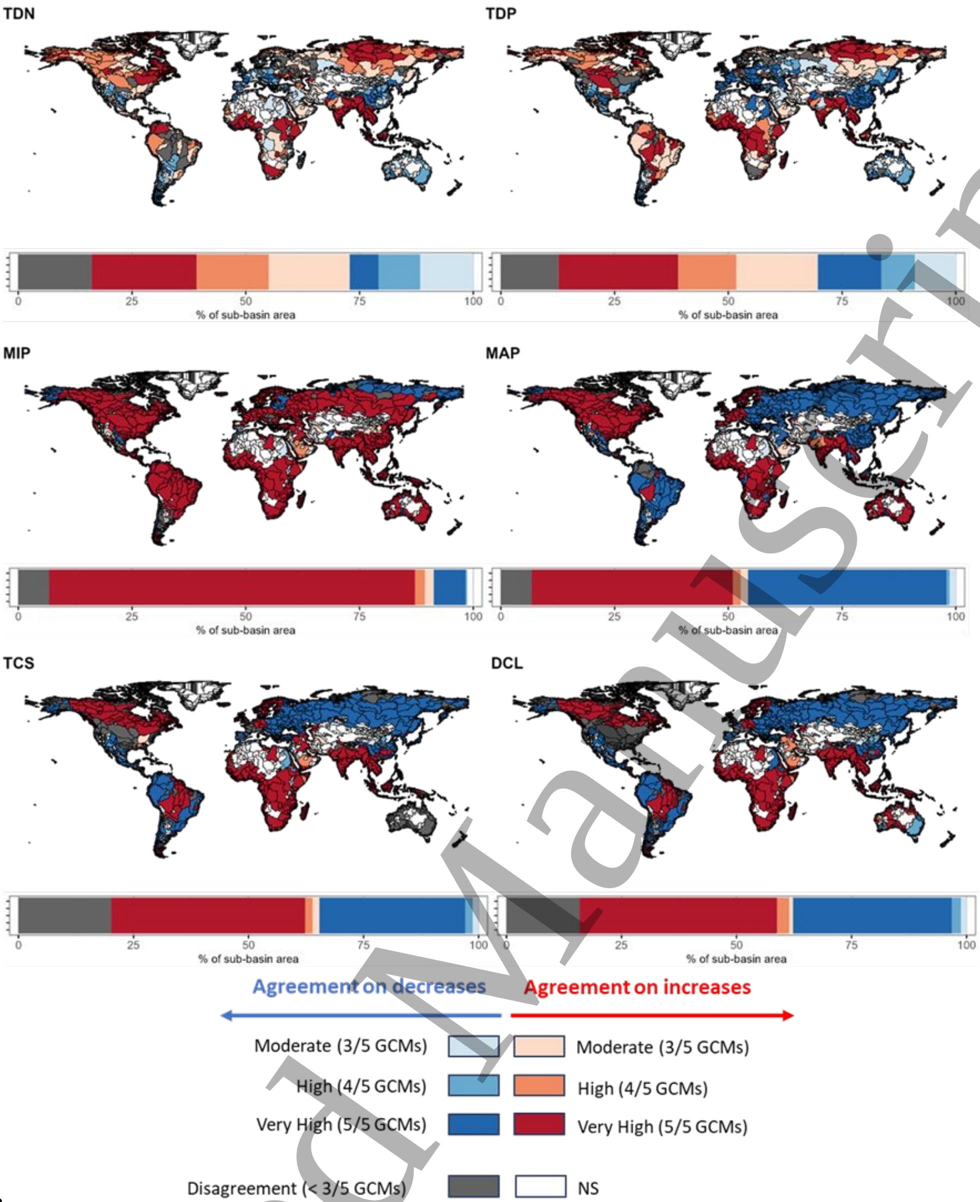
3.2 Inter-GCM agreements (Stage 2)

Our results show inter-GCM agreements for over 80% of the sub-basin areas globally (Figure 3). These areas agree on the direction of change (increases or decreases) in future river exports of individual pollutants between 2010 and 2050 for at least three GCMs (Table 1).

For increases in future pollution levels, 45-84% of sub-basin areas globally show moderate to very high inter-GCM agreement (Figure 3, Table 1 for definitions of the agreement classes). This range depends on pollutants. For increases in river exports of nutrients, approximately two-thirds of sub-basin areas show moderate to very high inter-GCM agreements, especially for many sub-basins of Southeast Asia, Sub-Saharan Africa, and parts of North America. For increases in river exports of plastics, very high inter-GCM agreements range from 47% (MIP) to 84% (MAP) of the sub-basin areas globally. For chemicals, these ranges are 45-50% (Figure 3). Many North American, Sub-Saharan African, and Southeast Asian sub-basins show very high inter-GCM agreements for increases in river exports of MAP and chemicals. Anthropogenic sources are expected to play an important role in sub-basins with moderate to very high inter-GCM agreements (on increases or decreases). This is because agricultural activities (e.g., fertilisers, animal manure, sewage) are projected to contribute 50% of TDN and 70% of TDP in coastal waters globally in 2050 (SI, Figure J.1). By 2050, household sources, such as laundry and dust, are expected to dominate MIP export by rivers (SI, Figure J.1).

For decreases in future pollution levels, 10-47% of sub-basin areas globally show moderate to very high inter-GCM agreements (Figure 3, Table 1). For nutrients, 32-34% of the sub-basin areas show moderate to very high inter-GCM agreements, particularly along the west coast of North America, Europe, Eastern Asia, and the east coast of Australia. Results show very high inter-GCM agreement on decreasing trends in river exports of plastics (10-47% of the area) and chemicals (35-42% of the area). This especially holds for many sub-basins of Europe and the east coast of North America. While many regions project increases in river exports of MIP by 2050 (see the previous paragraph), some sub-basins, especially in Eastern Asia, are expected to export less.

Disagreements among GCMs on future trends in river exports of pollutants are estimated for 5-20% of the sub-basin areas globally (Figure 3). For example, the lowest inter-GCM disagreement is estimated for future river exports of MIP (5% of the area) because of the greater effects of anthropogenic sources (e.g., household dust in sewage) compared to hydrology. For nutrients, the disagreements are estimated for over 15% of the sub-basin areas. This is primarily due to the large contribution of natural sources to future nutrient pollution in those areas (SI, Figure J.1). The highest disagreement is, however, estimated for future river exports of chemicals (15-20% of the global surface areas).



c

Figure 3: *Inter-GCM agreements for the direction of change (increases or decreases) in river exports of individual pollutants between 2010 and 2050 at the sub-basin scale. Maps show sub-basins for which three (moderate agreement), four (high agreement), or five (very high agreement) GCMs agree on the direction of change or sub-basins for which less than three GCMs agree (disagreement) on the direction of change. For more details regarding agreement classes see Table 1. Horizontal bars show the share of the global sub-basin area for each agreement class (Table 1). This shows the results using a 5% threshold for changes in river export of pollutants to determine the direction of change (see SI I, for results using a 1% and 10% threshold). GCMs are short for global climate models. Pollutants include total dissolved nitrogen (TDN), total dissolved phosphorus (TDP), microplastics (MIP), macroplastics (MAP), triclosan (TCS), and diclofenac (DCL). 2050 is based on Shared Socioeconomic Pathway 5 (rapid urbanisation and high economic development) and Representative Concentrative Pathway 8.5 (high global warming). NS (Not part of the Study area) denotes sub-basins that are not part of our study area as they do not drain into the seas or are part of Greenland (see SI, Figure E.1 for details). Source: the MARINA-Multi model (see Section 2 for the model and scenario descriptions).*

3.3 Multi-pollutant agreements (Stage 3)

For most of the global sub-basin areas, multi-pollutant agreements (≥3 GCMs for ≥3 pollutants, Table 1) are estimated for increases or decreases in river exports by 2050 (Figure 4). For increases, very high multi-pollutant agreements cover regions such as Sub-Saharan Africa, South Asia, and Subarctic North America (Table 1 for agreement classes). High agreements predominantly cover regions like Eastern South America, parts of the United States, and Europe. For decreases, very high agreements appear in scattered locations and high agreements are prevalent in large parts of Asia, Mexico and parts of Europe and South America. For both directions (increases and decreases), areas of moderate agreement are scattered.

Diverging trends or disagreements cover parts of Northern Asia and Southern America or parts of North America. This implies that, although inter-GCM agreements exist for individual pollutants, their responses to urbanisation and climate change vary among areas. Those regions are often characterised by increases in river exports of nutrients, and MIP, whereas MAP and chemicals are projected to decrease by 2050. Contrarily, areas of multi-pollutant disagreement are often associated with prominent inter-GCM disagreements for individual pollutants, indicating the presence of climate-driven uncertainties.

Multi-pollutant agreements on future trends for 2050 differ among seas (Figure 4, pies). This specifically holds for coastal waters of the Indian Ocean and the Mediterranean Sea, which show opposite trends. Projections for the Indian Ocean show multi-pollutant agreements on increases for 81% of its drainage area (Figure 4). In contrast, for the Mediterranean Sea, multi-pollutant agreements are on decreases for 64% of its drainage area. This differs among other coastal waters. For the coastal waters of the Atlantic Ocean, multi-pollutant agreements on increases in future pollution are estimated for nearly two-thirds of its drainage area. In the Pacific Ocean, this is for 41% of the drainage area, whereas 33% agrees on decreases and 18% show diverging trends. The Arctic Ocean has a mix of multi-pollutant agreements (Figure 4).

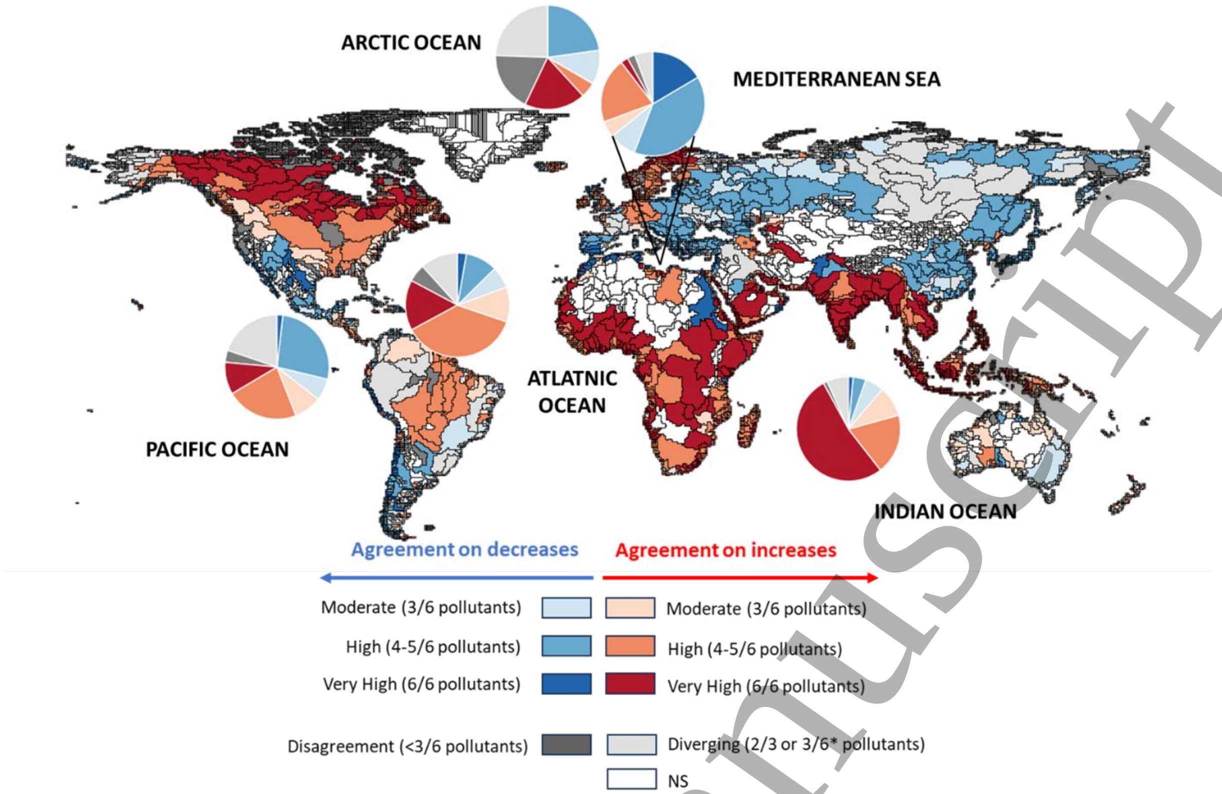


Figure 4: *Multi-pollutant agreements on the direction of change (increases or decreases) in their river exports between 2010 and 2050. The map shows the multi-pollutant agreement (as defined in Table 1) in the direction of change in river exports for at least three GCMs across six pollutants in a spatially explicit way. The pies show the area share of multi-pollutant agreement classes for five large seas in the world (i.e. see SI, Figure E.1 for a specification of the drainage areas by sea). Multi-pollutant agreement classes include: moderate (3/6 pollutants agree) high (4-5/6 pollutants agree), and very high (6/6 pollutants agree), disagreement (<3 pollutants agree) and diverging (an equal number of pollutants, i.e. 2/6 or 3/6 pollutants, agree on each direction). See Table 1 for details on agreement classes. NS (Not part of the Study area) denotes sub-basins that are not part of our study area as they do not drain into the seas or are part of Greenland (see SI, Figure E.1 for details). Pollutants include total dissolved nitrogen (TDN), total dissolved phosphorus (TDP), microplastics (MIP), macroplastics (MAP), triclosan (TCS), and diclofenac (DCL). Source: the MARINA-Multi model (see Section 2 for the model and scenario descriptions).*

4. Discussion

4.1 Water quality in a changing climate

Climate change affects the water cycle, and in turn, the water quality. Although hydrological changes remain uncertain[52,53], inter-GCM agreements highlight hotspots of future wetter and drier conditions[54] (selected examples of agreement approaches in SI D). Under RCP 8.5 (high emissions), approximately five billion people could experience substantial shifts in precipitation patterns by 2100[54]. Comparing Trancoso et al.'s[54] agreements in water quantity trends with our agreements on water quality trends (Figures 3-4, SI I), we find that some wetting regions (e.g. Northern Europe, and Northern America) show increasing pollution levels. Yet, this does not apply to all areas, implying that socio-economic drivers play an important role in water quality trends[17,18,39]. Generally, arid areas (e.g., Saharan Africa or Australia) show relatively low wetting or drying agreements[54,55]. This aligns with our findings of greater variability in natural river discharge (higher CV, see SI F) and pollutant exports (higher CV in Figure 2). As we used 10-year averaged hydrological inputs for five GCMs, our sample size was relatively small and may have introduced biases in our CV results. While averaging reduced the effect of cascading uncertainties (SI, Figure L.3), we may have under- or overestimated uncertainties related to dry and wet years (SI, Figures L.1-L.2). The main message remains unchanged when accounting for yearly hydrological inputs (55 model runs, SI, Figure L.2), while the results require careful interpretation.

Our results show that in an economically driven future with reactive environmental management and high-emissions (SSP5-RCP8.5), river exports of studied pollutants will increase globally, with greater climate-induced uncertainty in model simulations across all analysed regions. This highlights the need to act. This especially holds for areas like Sub-Saharan Africa, where monitoring data are lacking[17], pollution levels are projected to increase substantially, and model uncertainty is greatest (Figure 2). In regions with high river exports of pollutants, investments might be useful to focus on greater political and public awareness of water quality issues[31], along with identifying and implementing effective solutions to tackle regional pollution challenges. This requires an understanding of climate-driven hydrological uncertainties in water quality models (this study), drivers of pollution in hotspot areas[56], technological developments[57,58], alternative treatment pathways (e.g. constructed wetlands)[59], and awareness campaigns[60-62]. In areas with higher climate-induced uncertainties, investments could be useful in mitigating climate-related water quality risks via monitoring strategies that ensure accessible and transparent outputs. For example, accessible monitoring data could help to enhance our understanding of prominent issues today (i.e., evaluation of current status and supporting decision-making), while preparing for arising issues in the decades to come (i.e., reduce uncertainties in global water quantity and quality models)[63]. In Figure M.1 of the SI, we show that an alternative future with proactive environmental management and low-emissions (SSP1-RCP2.6) can substantially limit pollution and climate-induced uncertainty. Examples include monitoring campaigns for areas with higher climate-driven hydrological uncertainties, targeted research, and implementation of effective pollution reduction strategies.

This study contributes to improving the transparency and robustness of simplified global water quality models. Our water quality model simulates pollutant inputs from land to river and river exports to coastal waters under climate-driven hydrological changes (see Figure 1 and SI Figure N.1 and SI A and N for descriptions of the approach). However, land-to-river transport processes, such as nutrient runoff, weathering of P-contained minerals, and leaching of organic matter are treated in a simplified and static manner. They are not dynamically modelled in response to climate change, which limits their physical representations when simulating total pollutant export estimates. The goal of this study is narrower: to quantify how climate-driven hydrological changes affect annual river export loads of nutrients, plastics, and chemicals at the sub-basin scale by 2050, relative to 2010, under a high-end warming scenario (SSP5-RCP8.5). This is achieved using the soft-coupled VIC-MARINA-Multi framework. By isolating hydrological drivers, we are able to assess how uncertainties in future hydrology propagate through the modelling chain and influence the robustness of global river export projections. We foresee the benefits of more integrated water quality assessments (e.g. better representation of dynamic climate-sensitive terrestrial processes) by linking large-scale water quality models with advanced Terrestrial or Earth Systems Models. For instance, LM3-TAN[64] or the Community Land Model[65], could complement large-scale water quality models as they offer a detailed representation of terrestrial processes and biogeochemical cycling. However, such models often do not account for emerging pollutants such as plastics and chemicals. They are often computation-heavy. Moreover, the global water quality modelling community is still in an early stage of development. As such, this level of integration is beyond the scope of this study. Future work should aim to incorporate these climate-sensitive processes to further improve the robustness of large-scale water quality projections under climate change.

4.2 Model uncertainties and their propagation

Our models contain uncertainties in inputs, parameters, structure, outputs, and scenarios. When coupled, these uncertainties propagate through the system, compounding their influence on the accuracy and interpretation of results. Below, we analyse the individual model uncertainties and illustrate how they propagate across the modelling chain.

Individual model uncertainties

GCMs simplify complex climate systems with different levels of complexity (Table O.1) and are based on limited knowledge of some key climate variables. This introduces structural and parameter uncertainties, which could lead to a range in long-term projections[66]. Hence, using model ensembles is widely recommended to capture a broader range of possible outcomes. Although using more models (e.g., 10) could improve peak streamflow predictions[30], our five selected GCMs effectively captured the overall variability as they represent a wide range of simulation projections[67,68] (Table O.1). Uncertainties in the hydrological simulations of the VIC model are well-studied[35] (see Liang et al.[34] for details on validation and Van Vliet et al.[35] for a hydrological model intercomparison) and originate from three main sources: inherent structural differences in GCMs that affect input data (structural/input uncertainties), downscaling of GCM outputs (scenario uncertainties), and simplification of hydrological processes (structural uncertainties). Additionally, knowledge gaps in hydrological parameters contribute to parameter uncertainties[35]. While relying on a single hydrological model and a single water quality model ensures internal consistency, it limits the ability to explore structural variability.

Future studies could address this limitation by integrating multiple hydrological models. Uncertainties in MARINA-Multi are addressed[13,16,18] and mainly related to structure (e.g., deterministic model), parameterisation (e.g., hydrological sensitivity of model parameters, see SI C), and model inputs (e.g., river discharge[69]). This inherently limits its ability to capture dynamic water quality processes. Yet, the model is strong in analysing source attributions and scenario analyses to support policy-relevant questions on multi-pollutant reductions. To build trust in its projections, the MARINA-Multi model has been validated for the year 2010 against historical data[13,16] (see Table B.2). Its reliability for future assessments has also been evaluated through comparisons with other global and regional (Africa) modelling efforts[16,18] (see Table B.2). A comprehensive description of the model's structure, equations, and the outcomes of both validation and evaluation are available in Micella et al.[18]. Finally, all models are also subject to scenario uncertainty, as storylines, such as those represented by SSPs[36] and RCPs[37], can influence projections.

Propagation of uncertainties in the modelling chain

Understanding the propagation of uncertainties throughout the modelling chain is essential for multi-pollutant assessments. Hence, we evaluated the relative sensitivity of the MARINA-Multi model to variations in inputs across the modelling chain (SI K-L). First, GCM uncertainties propagate into the VIC model. For instance, river discharge projections based on the HadGEM model consistently yielded the highest river exports across pollutants. Conversely, the NorESM or MIROC models often generated the lowest river exports across pollutants (see SI, Table K.1). This may be explained by their differences in climate forcings (e.g. greenhouse gas scenarios)[28] and variations in atmospheric process modelling[29]. Second, uncertainties propagate further into the MARINA-Multi model. We first projected pollutant inputs to rivers by GCM-driven hydrology (see SI Figure N.1), which already revealed a spread in inputs, particularly for nutrients (see SI Figure N.2). This may be explained by the influence of diffuse sources, which are strongly driven by surface runoff[2,18] (see Box N.1). This especially holds for low-discharge conditions, where rainfall variability amplifies discharge fluctuations[70,71]. Then, we account for pollutant retention processes in rivers, reservoirs and through water consumption to quantify the river exports of pollutants to seas among the 5 GCMs. The spread in river exports indicates a stronger influence of uncertainties on nutrients (e.g. 50-54 Tg for TDN) compared to plastics and chemicals (e.g. 396-416 ton for TCS; see SI, Table K.1). Moreover, uncertainties are larger for projections of pollutant exports by rivers than for pollutant inputs to the rivers. Here, climate-driven uncertainties for pollutants from point sources are mainly related to retention/removal processes in rivers and reservoirs, which depend on discharge and water residence times[15,18]. Despite cascading uncertainties, the MARINA-Multi model remains robust. Its consistency, partly due to its simplicity, reinforces its credibility in identifying climate-driven hydrological changes which affect pollutant flows and key processes. Understanding uncertainty propagation allows us to refine models and improve techniques, ensuring reliable, policy-relevant insights.

4.3 Reflection on a new multi-pollutant building trust approach

We identified three principles to keep in mind when building trust in large-scale multi-pollutant models under climate-driven hydrological changes.

Principle 1: Be aware of the strengths and limitations of large-scale water quality models. Our modelling system's strengths include its ability to simulate multiple pollutants simultaneously, for past and future years while accounting for climate-driven hydrological uncertainties (knowledge gap 1, Section 1). This enables analyses of pollutant behaviour and trends while keeping computational demands low, making results accessible. However, simplicity also limits resolution and affects hydrological sensitivity across pollutants. For example, phosphorus appears to be the most sensitive and microplastics least sensitive (see Section 3.1 and SI, Table K.1 and Boxes N.1-N.2), potentially contributing to cascading uncertainties (Section 4.2). For example, as dynamics in climate-driven terrestrial pollutant flows are not represented explicitly, this limits our capacity to model total pollutant export by rivers dynamically. In our study, this was not the aim. Our modelling system enhances understanding of global water quality trends under climate-driven hydrological changes and extends to broader environmental challenges. By leveraging ISIMIP hydrological data, we can generate insights relevant to multiple sectors, including lakes and ecosystems (as demonstrated by Tigli et al.[9]).

Principle 2: Select evaluation strategies based on pollutants and model purpose. Validation is commonly used to evaluate models, yet dependent on monitoring data and, therefore, may not be ideal for building trust in emerging pollutants, data-scarce regions, and future trends[32]. Hence, the applicability of evaluation strategies may depend on the selected pollutants and the model's purpose. Strokal et al.,[32] identified 13 model evaluation strategies (overview in SI Table B.1). Yet, these strategies do not explicitly account for building trust under uncertainties associated with climate-driven hydrological changes (knowledge gap 2, Section 1). Our proposed three-stage approach (Section 2.3) can complement the 13 strategies as identified by Strokal et al.,[32] as it focuses on understanding the extent to which emergent trends in water pollution are robust across a range of GCMs and pollutants. Herewith, it proves a broader, integrative perspective on uncertainty than conventional sensitivity analysis offers. For example, while our approach involves varying model inputs, it differs from sensitivity analysis in both purpose and execution (see Table B.1 and Box B.1 in the SI). While we used VIC and MARINA-Multi, our approach is adaptable to other models in frameworks like ISIMIP. An example of this is the application to the DynQual model[72].

Principle 3: Clear and transparent communication reinforces trust. With this study, we have built trust in multi-pollutant projections under climate-driven hydrological changes. Yet, our results remain an abstraction of environmental systems, including their cascading uncertainties, and, therefore, should be treated carefully. By presenting results, their uncertainties, and the potential implications of those uncertainties clearly and transparently, we can reinforce trust. Avoiding jargon, indicating the model's purpose, and providing context to model evaluation results is essential for correct interpretation and effective communication with other scientific disciplines and policymakers. This aids in a wide understanding of uncertainties associated with climate-driven hydrological changes in pollution management. Enabling identification of context-specific solutions to future water quality issues amid growing pressure on climate, environmental systems, and society.

5. Conclusion

We developed and applied a three-stage approach to build trust in future river exports worldwide under climate-driven hydrological changes for nutrients, plastics, and chemicals, simultaneously. For this, we used a soft-coupled water quantity (VIC) and water quality (MARINA-Multi) model system, driven by five Global Climate Models under a high global warming scenario (RCP8.5). We ran the MARINA-Multi model with VIC hydrological outputs for each GCM to quantify river exports of pollutants to seas for 2010 and 2050. In arid regions such as the Middle East, East Asia, and Northern Africa, climate-driven uncertainties play a key role in future river pollutant exports. For many African sub-basins, high increases in river exports of pollutants are projected by 2050 under high climate-driven uncertainties. Globally, over 80% of the sub-basin areas agree on future trends, either increasing or decreasing, in river exports of individual pollutants for at least three GCMs. Multi-pollutant agreements on future trends differ among seas: 53% of the area agrees on increasing river exports of six pollutants into the Indian Ocean by 2050, whereas 17% agrees on decreasing trends for the Mediterranean Sea. Our approach builds trust in future multi-pollutant trends under climate-driven hydrological changes, strengthening global water quality assessments. Providing clear and transparent information on climate-driven hydrological uncertainties improves awareness and supports the effective use of water quality model outputs for well-informed actions.

Acknowledgements

We would like to acknowledge the participants of the Water Quality sector meeting and workshops within the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) in Prague (2023), Wageningen (2023, 2024), and Potsdam (2024) for their ideas and discussions on water quality modelling that contributed to this manuscript. We acknowledge the use of ChatGPT (version GPT-4o) as a support tool to enhance efficiency for coding in R and Python for data visualisation. IM and MS have received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement 956623. MPB acknowledges funding from Wageningen Institute for Environment and Climate Research (WIMEK) scholarship project 5160958452. ERJ and MTHvV were financially supported by the European Research Council (ERC) under the European Union's Horizon Europe research and innovation program (grant agreement 101039426, B-WEX) and the Netherlands Scientific Organisation (NWO) by a VIDI grant (VI.Vidi.193.019).

Data availability statement

The data supporting this study's findings are publicly available in the DANS-EASY repository: https://doi.org/10.17026/PT/4XLIBQ (DOI will be activated after acceptance/during the revision stage).

References

1. Strokal M, Spanier JE, Kroeze C, Koelmans AA, Flörke M, Franssen W, et al. Global multi-pollutant modelling of water quality: scientific challenges and future directions. Current opinion in environmental sustainability. 2019;36:116-25.

2. Li Y, Wang M, Chen X, Cui S, Hofstra N, Kroeze C, et al. Multi-pollutant assessment of river pollution from livestock production worldwide. Water Research. 2022;209:117906.

3. Wang M, Zhang Q, Li Y, Bak M, Feng S, Kroeze C, et al. Water pollution and agriculture: Multi-pollutant perspectives. Frontiers of Agricultural Science and Engineering. 2023;10(4):639-47.

4. Kroeze C, Gabbert S, Hofstra N, Koelmans AA, Li A, Löhr A, et al. Global modelling of surface water quality: a multi-pollutant approach. Current opinion in environmental sustainability. 2016;23:35-45.

5. Strokal M, Kroeze C, Wang M, Bai Z, Ma L. The MARINA model (Model to Assess River Inputs of Nutrients to seAs): Model description and results for China. Science of the Total Environment. 2016;562:869-88.

6. Li Y, Zhang Q, Baartman J, van Wijnen J, Beriot N, Kroeze C, et al. The plastic age: river pollution in china from crop production and urbanization. Environmental Science & Technology. 2023;57(32):12019-32.

7. Van Wijnen J, Ragas AMJ, Kroeze C. River export of triclosan from land to sea: a global modelling approach. Science of the Total Environment. 2018;621:1280-8.

8. Van Wijnen J, Ragas AMJ, Kroeze C. Modelling global river export of microplastics to the marine environment: Sources and future trends. Science of the Total Environment.

2019;673:392-401.

9. Tigli M, Bak MP, Janse JH, Strokal M, Janssen ABG. The future of algal blooms in lakes globally is in our hands. Water Research. 2025;268:122533.

10. Li H-M, Tang H-J, Shi X-Y, Zhang C-S, Wang X-L. Increased nutrient loads from the Changjiang (Yangtze) River have led to increased harmful algal blooms. Harmful Algae. 2014;39:92-101.

11. Koelmans AA, Bakir A, Burton GA, Janssen CR. Microplastic as a vector for chemicals in the aquatic environment: critical review and model-supported reinterpretation of empirical studies. Environmental science & technology. 2016;50(7):3315-26.

12. Díaz-Cubilla M, Letón P, Luna-Vázquez C, Marrón-Romera M, Boltes K. Effect of carbamazepine, ibuprofen, triclosan and sulfamethoxazole on anaerobic bioreactor performance: Combining cell damage, ecotoxicity and chemical information. Toxics. 2022;10(1):42.

13. Micella I, Kroeze C, Bak MP, Strokal M. Causes of coastal waters pollution with nutrients, chemicals and plastics worldwide. Marine Pollution Bulletin. 2024;198:115902.

14. Bouwman AF, Bärlund I, Beusen AHW, Flörke M, Gramberger M, Cardona JR, et al. Multimodel and multiconstituent scenario construction for future water quality. Environmental Science & Technology Letters. 2024;11(12):1272-80.

15. Bak MP, Kroeze C, Janssen ABG, Strokal M. Modelling future coastal water pollution: impacts of point sources, socio-economic developments & multiple pollutants. Environmental Research Letters. 2024;19(6):064028.

16. Strokal M, Bai Z, Franssen W, Hofstra N, Koelmans AA, Ludwig F, et al. Urbanization: an increasing source of multiple pollutants to rivers in the 21st century. npj Urban sustainability. 2021;1(1):1-13.

17. Jones ER, Bierkens MFP, Van Puijenbroek PJTM, Van Beek LPH, Wanders N, Sutanudjaja EH, et al. Sub-Saharan Africa will increasingly become the dominant hotspot of surface water pollution. Nature Water. 2023;1(7):602-13.

18. Micella I, Kroeze C, Bak MP, Tang T, Wada Y, Strokal M. Future scenarios for river exports of multiple pollutants by sources and sub-basins worldwide: Rising pollution for the Indian Ocean. Earth's Future. 2024;12(11):e2024EF004712.

19. Van Vliet MTH, Franssen WHP, Yearsley JR, Ludwig F, Haddeland I, Lettenmaier DP, et al. Global river discharge and water temperature under climate change. Global Environmental Change. 2013;23(2):450-64.

20. Wang H, Liu J, Klaar M, Chen A, Gudmundsson L, Holden J. Anthropogenic climate change has influenced global river flow seasonality. Science. 2024;383(6686):1009-14.

21. Yasarer LMW, Sturm BSM. Potential impacts of climate change on reservoir services and management approaches. Lake and Reservoir Management. 2016;32(1):13-26.

22. Ehsani N, Vörösmarty CJ, Fekete BM, Stakhiv EZ. Reservoir operations under climate

change: Storage capacity options to mitigate risk. Journal of Hydrology. 2017;555:435-46.

23. Bodirsky BL, Popp A, Lotze-Campen H, Dietrich JP, Rolinski S, Weindl I, et al. Reactive nitrogen requirements to feed the world in 2050 and potential to mitigate nitrogen pollution. Nature communications. 2014;5(1):3858.

24. Beusen AHW, Bouwman AF. Future projections of river nutrient export to the global coastal ocean show persisting nitrogen and phosphorus distortion. Frontiers in Water. 2022;4:893585.

25. Nkwasa A, Chawanda CJ, Nakkazi MT, Tang T, Eisenreich SJ, Warner S, et al. One third of African rivers fail to meet the'good ambient water quality'nutrient targets. Ecological Indicators. 2024;166:112544.

26. UNEP. A snapshot of the world's water quality: towards a global assessment. UNEP; 2016.

27. Jones ER, Bierkens MFP, Wanders N, Sutanudjaja EH, Van Beek LPH, Van Vliet MT. DynQual v1. 0: a high-resolution global surface water quality model. Geoscientific Model Development. 2023;16(15):4481-500.

28. Lehner F, Deser C, Maher N, Marotzke J, Fischer EM, Brunner L, et al. Partitioning climate projection uncertainty with multiple large ensembles and CMIP5/6. Earth System Dynamics. 2020;11(2):491-508.

29. Flato G, Marotzke J, Abiodun B, Braconnot P, Chou SC, Collins W, et al. Evaluation of climate models. Climate change 2013: the physical science basis Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change: Cambridge University Press; 2013. p. 741-866.

30. Wang HM, Chen J, Xu CY, Zhang J, Chen H. A framework to quantify the uncertainty contribution of GCMs over multiple sources in hydrological impacts of climate change. Earth's Future. 2020;8(8):e2020EF001602.

31. Jones ER, Graham DJ, Van Griensven A, Flörke M, Van Vliet MTH. Blind spots in global water quality monitoring. Environmental Research Letters. 2024;19(9).

32. Strokal M, Wang M, Micella I, Janssen ABG. Building trust in large-scale water quality models: 13 alternative strategies beyond validation. Discover Water. 2024;4(1):82.

33. Gleeson T, Wagener T, Döll P, Zipper SC, West C, Wada Y, et al. GMD perspective: The quest to improve the evaluation of groundwater representation in continental-to global-scale models. Geoscientific Model Development. 2021;14(12):7545-71.

34. Liang X, Lettenmaier DP, Wood EF, Burges SJ. A simple hydrologically based model of land surface water and energy fluxes for general circulation models. Journal of Geophysical Research: Atmospheres. 1994;99(D7):14415-28.

35. Van Vliet MTH, Van Beek LPH, Eisner S, Flörke M, Wada Y, Bierkens MFP. Multi-model assessment of global hydropower and cooling water discharge potential under climate change. Global Environmental Change. 2016;40:156-70.

36. O'Neill BC, Kriegler E, Ebi KL, Kemp-Benedict E, Riahi K, Rothman DS, et al. The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. Global environmental change. 2017;42:169-80.

37. Van Vuuren DP, Edmonds J, Kainuma M, Riahi K, Thomson A, Hibbard K, et al. The representative concentration pathways: an overview. Climatic change. 2011;109:5-31.

38. O'Neill BC, Carter TR, Ebi K, Harrison PA, Kemp-Benedict E, Kok K, et al. Achievements and needs for the climate change scenario framework. Nature climate change. 2020;10(12):1074-84.

39. Van Vliet MTH, Thorslund J, Strokal M, Hofstra N, Flörke M, Ehalt Macedo H, et al. Global river water quality under climate change and hydroclimatic extremes. Nature Reviews Earth & Environment. 2023;4(10):687-702.

40. Taylor KE, Stouffer RJ, Meehl GA. An overview of CMIP5 and the experiment design. Bulletin of the American meteorological Society. 2012;93(4):485-98.

41. Hempel S, Frieler K, Warszawski L, Schewe J, Piontek F. A trend-preserving bias correction–the ISI-MIP approach. Earth System Dynamics. 2013;4(2):219-36.

42. Watanabe S, Hajima T, Sudo K, Nagashima T, Takemura T, Okajima H, et al. MIROC-ESM 2010: model description and basic results of CMIP5-20c3m experiments. Geoscientific Model Development. 2011;4(4):845-72.

43. Dufresne JL, Foujols MA, Denvil S, Caubel A, Marti O, Aumont O, et al. Climate change projections using the IPSL-CM5 Earth System Model: from CMIP3 to CMIP5. Climate Dynamics. 2013;40(9-10):2123-65.

44. Collins WJ, Bellouin N, Doutriaux-Boucher M, Gedney N, Halloran P, Hinton T, et al. Development and evaluation of an Earth-System model – HadGEM2. Geoscientific Model Development. 2011;4(4):1051-75.

45. Bentsen M, Bethke I, Debernard JB, Iversen T, Kirkevåg A, Seland Ø, et al. The Norwegian Earth System Model, NorESM1-M – Part 1: Description and basic evaluation of the physical climate. Geoscientific Model Development. 2013;6(3):687-720.

46. Dunne JP, John JG, Shevliakova E, Stouffer RJ, Krasting JP, Malyshev SL, et al. GFDL's ESM2 Global Coupled Climate–Carbon Earth System Models. Part II: Carbon System Formulation and Baseline Simulation Characteristics*. Journal of Climate. 2013;26(7):2247-67.

47. Van Vliet MTH, Wiberg D, Leduc S, Riahi K. Power-generation system vulnerability and adaptation to changes in climate and water resources. Nature Climate Change. 2016;6(4):375-80.

48. Hamlet AF, Lettenmaier DP. Effects of climate change on hydrology and water resources in the Columbia River Basin 1. JAWRA Journal of the American Water Resources Association. 1999;35(6):1597-623.

49. Nijssen B, O'Donnell GM, Hamlet AF, Lettenmaier DP. Hydrologic sensitivity of global rivers to climate change. Climatic change. 2001;50:143-75.

50. Wood AW, Lettenmaier DP. A test bed for new seasonal hydrologic forecasting approaches in the western United States. Bulletin of the American Meteorological Society. 2006;87(12):1699-712.

51. Voisin N, Kintner-Meyer M, Wu D, Skaggs R, Fu T, Zhou T, et al. Opportunities for joint water–energy management: sensitivity of the 2010 Western US Electricity Grid Operations to Climate Oscillations. Bulletin of the American Meteorological Society. 2018;99(2):299-312.

52. Melsen LA, Addor N, Mizukami N, Newman AJ, Torfs PJJF, Clark MP, et al. Mapping (dis) agreement in hydrologic projections. Hydrology and Earth System Sciences. 2018;22(3):1775-91.

53. Wu Y, Miao C, Slater L, Fan X, Chai Y, Sorooshian S. Hydrological projections under CMIP5 and CMIP6: Sources and magnitudes of uncertainty. Bulletin of the American Meteorological Society. 2024;105(1):E59-E74.

54. Trancoso R, Syktus J, Allan RP, Croke J, Hoegh-Guldberg O, Chadwick R. Significantly wetter or drier future conditions for one to two thirds of the world's population. Nat Commun. 2024;15(1):483.

55. Nkwasa A, Chawanda CJ, Schlemm A, Ekolu J, Frieler K, Van Griensven A. Historical climate impact attribution of changes in river flow and sediment loads at selected gauging stations in the Nile basin. Climatic Change. 2024;177(3):42.

56. Micella I, Bak MP, Dürr HH, Jones ER, Kumar R, Nkwasa A, et al. Uneven distribution of multi-pollutant hotspots worldwide: river exports to seas and their global change drivers in the future. Environmental Research Water (Focus Issue: Focus on Model Intercomparisons of Water Quality Under Global Change Impacts). under review.

57. Deletic A, Wang H. Water pollution control for sustainable development. Engineering. 2019;5(5):839-40.

58. Obaideen K, Shehata N, Sayed ET, Abdelkareem MA, Mahmoud MS, Olabi A. The role of wastewater treatment in achieving sustainable development goals (SDGs) and sustainability guideline. Energy Nexus. 2022;7:100112.

59. Ghadouani A, Coggins LX. Science, technology and policy for water pollution control at the watershed scale: current issues and future challenges. Physics and Chemistry of the Earth, Parts A/B/C. 2011;36(9-11):335-41.

60. Seelen LM, Flaim G, Jennings E, Domis LNDS. Saving water for the future: Public awareness of water usage and water quality. Journal of environmental management. 2019;242:246-57.

61. Borawska A. The role of public awareness campaigns in sustainable development. Economic and Environmental Studies. 2017;17(4 (44)):865-77.

62. Riley R, de Preux L, Capella P, Mejia C, Kajikawa Y, de Nazelle A. How do we effectively communicate air pollution to change public attitudes and behaviours? A review. Sustainability Science. 2021:1-21.

63. Freni G, Mannina G, Viviani G. Role of modeling uncertainty in the estimation of climate and socioeconomic impact on river water quality. Journal of water resources planning and management. 2012;138(5):479-90.

64. Lee M, Shevliakova E, Stock CA, Malyshev S, Milly PC. Prominence of the tropics in the recent rise of global nitrogen pollution. Nature communications. 2019;10(1):1437.

65. Lawrence DM, Fisher RA, Koven CD, Oleson KW, Swenson SC, Bonan G, et al. The Community Land Model version 5: Description of new features, benchmarking, and impact of forcing uncertainty. Journal of Advances in Modeling Earth Systems. 2019;11(12):4245-87.

66. Knutti R, Baumberger C, Hirsch Hadorn G. Uncertainty quantification using multiple models—Prospects and challenges. Computer simulation validation: Fundamental concepts, methodological frameworks, and philosophical perspectives. 2019:835-55.

67. McSweeney CF, Jones RG. How representative is the spread of climate projections from the 5 CMIP5 GCMs used in ISI-MIP? Climate Services. 2016;1:24-9.

68. Warszawski L, Frieler K, Huber V, Piontek F, Serdeczny O, Schewe J. The inter-sectoral impact model intercomparison project (ISI–MIP): project framework. Proceedings of the National Academy of Sciences. 2014;111(9):3228-32.

69. Wang M, Kroeze C, Strokal M, van Vliet MTH, Ma L. Global change can make coastal eutrophication control in China more difficult. Earth's Future. 2020;8(4):e2019EF001280.

70. Diffenbaugh NS, Giorgi F. Climate change hotspots in the CMIP5 global climate model ensemble. Clim Change. 2012;114(3-4):813-22.

71. Gnann S, Reinecke R, Stein L, Wada Y, Thiery W, Müller Schmied H, et al. Functional relationships reveal differences in the water cycle representation of global water models. Nature Water. 2023;1(12):1079-90.

72. Strokal M, et al. A framework for model intercomparisons of water quality under global change: community building and new opportunities. Environmental Research Water (Focus Issue: Focus on Model Intercomparisons of Water Quality Under Global Change Impacts). in revision.