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Uneven distribution of multi-pollutant hotspots worldwide: river exports to seas and their global change drivers in the future

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Abstract

Water pollution with nutrients, chemicals, and plastics seriously threatens coastal ecosystems and populations. This multi-pollutant problem is driven by urbanization, food demand, and human-induced changes. Socio-economic disparities exacerbate these issues, with low- and middle-income regions typically facing greater pollution levels due to inadequate management systems. Progress in addressing multi-pollutant problems remains uneven worldwide. Here, we aim to identify future multi-pollutant hotspots of coastal waters and analyse their spatial distribution patterns associated with socio-economic drivers across global income levels. For this, we apply the existing Model to Assess River Inputs of pollutaNts to Seas to quantify river exports of nutrients (nitrogen & phosphorus), plastics (micro & macro), and chemicals (triclosan & diclofenac) by sub-basin and source for 2010 and 2050. Model inputs were aggregated to sub-basins and derived largely from existing datasets and other integrated models. This study shows that, globally, river exports of pollutants to coastal waters are projected to increase by 2050, although this trend is not consistent across all sub-basins and pollutant types. Thus, future multi-pollutant hotspots of coastal waters are expected to be unevenly distributed worldwide. For many Asian coastal waters, multi-pollutant hotspots are projected because of high pollution levels in 2050, which are largely associated with increased fertilizer use. For many African coastal waters, multi-pollutant hotspots are projected because of rapid increases in pollution levels over 2010–2050 that are driven by rapid population growth and poor waste management. Rapid urbanization drives pollution hotspots with plastics in high-income basins worldwide. Over 75% of the population in low-income basins is projected to live in future multi-pollutant hotspots. Our findings emphasize the need to address income-based disparities in pollution management and to support basin-based policies for equitable and sustainable water management worldwide.

1. Introduction

Water resources are increasingly affected by nutrients, chemicals, and plastics [1]. Global change is expected to influence future surface water availability through climate change impacts [2, 3], and pollute water resources through intensified socio-economic developments associated with urbanization, population growth, and agricultural practices [4, 5]. Rising pollution not only harms ecosystems but also undermines progress towards Sustainable Development Goals (SDGs) 6 (Clean Water for All) [6] and 14 (Life Below Water) [7]. Alarmingly, projections indicate major increases in population exposure to clean water scarcity [8], including a threefold rise in nitrogen-driven scarcity by 2050 under an economy-driven scenario [9], such as the combination of Shared Socioeconomic Pathway 5 (SSP 5) and Representative Concentration Pathway 8.5 (RCP 8.5) [10]. Furthermore, Micella *et al* [11] indicated that the loads of multiple pollutants to coastal waters are projected to double compared to a sustainability-driven scenario (i.e. SSP1-RCP2.6).

Large-scale water quality models have made progress in quantifying the river [12] and coastal water pollution [13] for a number of pollutants, yet findings show strong regional differences in pollutant types and trends [14]. Models that simultaneously compute river exports of multiple pollutants from land to sea via the river network are referred to as multi-pollutant models [15]. Model outcomes are reported in loads (e.g. kg yr^{-1}) and are often translated to yields (e.g. kg km^{-2} yr^{-1}) to facilitate comparisons among sub-basins worldwide. In our framework, we define a multi-pollutant problem as the simultaneous occurrence of hotspots for multiple pollutants (nutrients, plastics, and chemicals), as identified using our hotspot identification methods (see methods section).

Pollution disproportionately harms lower-income communities by worsening human and ecosystem health, food production, and economic inequalities [16]. Heavily polluted rivers can slow economic growth [17, 18]. High-income (HI) regions such as Europe and North America benefit from widespread access to safely managed drinking water [19] and from resources to effectively address water pollution. In contrast, over half of the population in regions such as Sub-Saharan Africa, South Asia, and South America lacks access to safely managed drinking water [20]. These regions also have limited financial resources and insufficient institutional capacity [21]. As a result, their vulnerability to water pollution is reported to be exacerbated [22]. Yet, while studies have assessed the economic costs of water pollution or focused on single sectors (e.g. drinking water) in HI regions [23], few studies have explored how income disparities drive coastal water pollution worldwide. While air pollution has been extensively studied in relation to socio-economic inequalities [24], the role of these inequalities in driving pollution from land-based activities to coastal waters remains largely unknown worldwide.

Existing studies assess overall pollution levels (e.g. for nutrients, chemicals, and plastics [1, 25]) but often overlook two key aspects. These are: (1) how multi-pollutant hotspots for coastal waters change over space and time, and (2) the socio-economic factors driving them. To clarify the first aspect, most global modelling approaches rely on a single-threshold method that focuses either on high pollution levels [26] or rapid increases [27]. Here, we introduce a dual hotspot approach that captures both persistent (with high pollution levels) and emerging (with high increases in pollution levels) hotspots, providing a more comprehensive view of multi-pollutant issues in the future. To clarify the second aspect, there is a need for models that track not only coastal water pollution trends and multi-pollutant hotspots but also their key drivers worldwide. Urbanization, for example, increases plastic and chemical pollution through poorly managed waste and untreated wastewater [13]. Agricultural activities contribute to nutrient pollution via fertilizer runoff and livestock waste [28]. Without a clear understanding of these drivers, particularly in vulnerable regions with low economic growth, identifying and implementing effective interventions remains difficult.

To address these knowledge gaps, this study aims to identify future multi-pollutant hotspots of coastal waters and analyse their spatial distribution patterns associated with socio-economic drivers across global income levels. To this end, we apply the existing MARINA-Multi (Model to Assess River Inputs of pollutaNts to seAs) model to quantify annual river exports of nutrients (nitrogen & phosphorus), plastics (macro & micro), and chemicals (triclosan (TCS) & diclofenac (DCL)) by sub-basin and source for 2010 and 2050. Our results provide insights into income-based susceptibilities to water pollution worldwide using a multi-pollutant modelling approach. Our analysis provides insights to inform sustainable and equitable water management strategies to support progress toward SDGs 6 and 14, and help bridge inequalities in resource allocation, particularly in areas with differing socio-economic and environmental challenges.

2. Methods

2.1. Multi-pollutant modelling

We studied the river exports of nutrients, chemicals, and plastics pollution to coastal waters. For this, we used the MARINA-Multi [11]. This global-scale model relies on steady-state, process-based and sub-basin-scale approaches to address multi-pollutant issues. The model covers 10 226 sub-basins. For our analysis of river exports, we excluded Greenland sub-basins and sub-basins that do not drain into the sea. As a result, pollutants reach coastal waters from 8 890 sub-basins. The model has been developed and evaluated for past conditions [29] and future scenarios [11]. The model is part of the MARINA model family with a 10 year history of building trust in its modelling approaches [30]. A detailed documentation of the model description and validation, including equations and inputs, is published in Micella *et al* [11] and supplementary information (SI) A.

River exports of pollutants are simulated as a function of pollutant inputs from point and diffuse sources into rivers (loads, kg yr^{-1}) and their export to the sub-basin outlets (loads, kg yr^{-1}) and then from the outlets to the river mouths (coastal waters, in loads, kg yr^{-1}). The following pollution types are considered:

- Nutrient: dissolved inorganic (DIN, DIP) and dissolved organic (DON, DOP) nitrogen (N) and phosphorus (P), which are then aggregated into total dissolved (TDN) nitrogen and phosphorus (TDP);
- Chemical: TCS and DCL;
- Plastic: microplastics (MIP) and macroplastics (MAP).

Inputs of these pollutants into rivers are simulated from point and diffuse sources. Point sources include sewage systems (all pollutants), direct discharges of animal manure (nutrients), and human waste (nutrients). They are modelled as functions of pollutant excretion or consumption rates per capita, population with sewage connections (and practicing open defecation if relevant), and removal fractions during wastewater treatment (except for estimates of open defecation). Diffuse sources are separated into anthropogenic and non-anthropogenic (natural). Diffuse sources are modelled as a function of pollutant inputs on land corrected for soil retention and annual runoff from land to rivers. Anthropogenic inputs on land include synthetic fertilizers, animal manure, atmospheric N deposition on agricultural land, biological N_2 fixation by crops, organic matter leaching, weathering of P-containing minerals, and mismanaged plastic waste. Non-anthropogenic sources include atmospheric N deposition on non-agricultural areas, biological N_2 fixation by natural vegetation, and organic leaching and weathering of P-containing minerals from non-agricultural areas. Pollutant export to outlets and river mouths is simulated as a function of annual runoff and river discharge, while accounting for in-river retention and losses through denitrification, sedimentation (most pollutants), damming (nutrients), and water abstraction (all pollutants). Retention is simulated using hydrological data, dam information and other sub-basin characteristics (see SI A).

We run the model at the sub-basin scale for 2010 and 2050 under an 'economy-driven' scenario, following the SSP5-RCP8.5 storyline of high-growth, fossil-fuel-driven development and a high-emission trajectory [31]. This scenario represents the upper bound of plausible futures and is commonly used to assess potential high-impact outcomes under intensive socio-economic and emission pressures, which justified our choice. The MARINA-Multi model uses specific hydrological (i.e. river discharges and runoff) inputs from the Variable Infiltration Capacity (VIC) model generated for each General Circulation Model (GCM) [32]. To represent each target year, we averaged hydrological inputs over 2005–2015 for 2010 and 2045–2055 for 2050 (see SI G). Inter-GCM variability in river pollutant exports (kg yr^{-1}) over these 10 year periods is reported in SI table G.1. For further analysis, we averaged outputs across five GCMs to focus on socio-economic drivers by income class. Climate-related hydrological uncertainties for river exports of multiple pollutants are discussed in Bak *et al* [33].

The input data at the sub-basin scale for the years 2010 and 2050 include various socio-economic, environmental, and hydrological parameters. Population data, including urban and rural distributions, Gross Domestic Product (GDP, US2010$/cap/year), and the Human Development Index (0–1) are from Strokal *et al* [1]. Sanitation and wastewater parameters, including treatment fractions, follow van Puijenbroek *et al* [34] with detergent and laundry contributions to P pollution from van Puijenbroek *et al* [35]. Wastewater treatment efficiencies (0–1) for TDN, TDP, MIP, TCS, and DCL follow Micella *et al* [29]. Per capita consumption of TCS, MIP, and DCL is from van Wijnen *et al* [36, 37] and Font *et al* [25], respectively, while mismanaged plastic waste (kg/cap/year) is from Lebreton and Andrady [38]. Agricultural data, such as fertilizer use and manure application on land, are from Beusen *et al* [39].

Hydrological data include natural and actual river discharges, runoff, and data on reservoirs and controlled lakes. Natural river discharges (km^3 yr^{-1}) for five GCMs are from van Vliet *et al* [32], which were bias-corrected following the trend-preserving ISIMIP approach [40]. Actual river discharges were calculated using the natural river discharge data and GCM-specific water consumption data from Khan *et al* [41]. Reservoir and lake data from Messager *et al* [42] were used to estimate nutrient retention.

2.2. Multi-pollutant analysis and hotspots

In this study, 'hotspots' are sub-basins that exhibit either disproportionately high or substantially increasing river exports of pollutants. These hotspots were classified as either persistent or emerging. Persistent hotspots exhibit high pollution levels in both the past and the future, as identified using a quantile-based approach. Emerging hotspots show higher pollution in the future than in the past, identified using a direction-based approach. These approaches were intentionally defined as relative measures, consistent with the study's focus. The quantile-based approach relies on probability distribution functions (PDFs) to analyse the river exports of six pollutants. Therefore, the approach accounts for pollution levels when defining hotspots. In contrast, the direction-based approach is built on relative changes in pollution levels over time. In this case, the increase in pollution levels from 2010 to 2050 can be used to define hotspots. We first defined pollution hotspots for individual pollutants and subsequently for multiple pollutants, as explained below. Finally, we combined the two approaches to identify overlaps for hotspots for single pollutants, which are sub-basins that are both 'highly' polluted and experiencing increasing pollution trends.

In the quantile-based approach (figure 1, approach 1), pollution hotspots were defined using a threshold of the 75th percentile derived from the PDFs. Sub-basins for which pollution levels (river exports) exceeded this threshold were considered persistent hotspots. We calculated PDFs for the river export of each pollutant in 2010. PDFs are the plot of river exports with the log10 yield (kg km^{-2} yr^{-1}) on the *X*-axis and the frequency of sub-basins within a given yield range on the *Y*-axis. The shape of the distribution curve indicates whether river exports are generally lower (right-skewed, clustering toward the left side of the distribution) or higher (left-skewed, clustering toward the right side of the distribution). In contrast, the height reflects the number of sub-basins that fall within a specific range (distribution density). The standard deviation (sd) determines how clustered the sub-basins are around the mean. Our threshold of the 75th percentile for the year 2010 (see SI table D.2 for absolute values) remains constant across sub-basins but varies by pollutant (figure 1, approach 1). We then applied this threshold to projections for 2050 and classified sub-basins as hotspots if their pollutant yields (e.g. kg km^{-2} yr^{-1}) in 2050 exceed the 75th percentile (of 2010), highlighting areas with already high pollution levels. In figures 1 and 2, shaded areas highlight river exports of pollutants in 2050 that exceed the 75th percentile of 2010 pollution levels. This threshold is arbitrary, but it highlights sub-basins with considerably higher pollution levels than the other sub-basins in a consistent way [26, 28, 43, 44]. To understand how this choice affected our main conclusions, we performed a sensitivity analysis with the 55th and 95th percentiles (see the SI figure G.1).

In the direction-based approach (figure 1, approach 2), pollution hotspots are defined using another threshold based on the relative changes in river exports of pollutants between the years 2010 and 2050. We set a threshold of at least a 30% increase by 2050 [1, 27, 45]. Sub-basins for which pollution levels (river exports) exceeded this threshold were considered an emerging hotspot (figure 1, approach 2). To justify the choice of this threshold and understand its influence on our results, we performed a sensitivity analysis with 10% and 50% increases between 2010 and 2050 (see the SI figure G.2). This approach highlights the sub-basins that are expected to experience considerable increases in pollution levels, even if their levels in 2010 are relatively low.

For both approaches, we identified multi-pollutant hotspots for the year 2050. A sub-basin is considered a multi-pollutant hotspot if at least two pollutants exceed their respective thresholds (75th percentile or a 30% increase between 2010 and 2050). Unlike Vörösmarty *et al* [46], who used expert-derived weights, we treated all six pollutants equally due to variability, context dependence [47], and uncertainty in pollutant impacts (e.g. plastics) [48]. Altogether, this resulted in a comprehensive assessment of multi-pollutant patterns, identifying both high-pollution sub-basins (quantile-based approach) and sub-basins where pollutant loads are likely to increase rapidly (direction-based approach).

2.3. Income levels and global change drivers

Income levels: We examined the future distribution of multi-pollutant hotspots across income levels using the direction-based approach. This approach was used for in-depth analysis for two reasons. First, the direction-based approach enables us to cover sub-basins that today have low pollution levels but may become hotspots in the future. Second, we aim to provide insights into sub-basins that require urgent

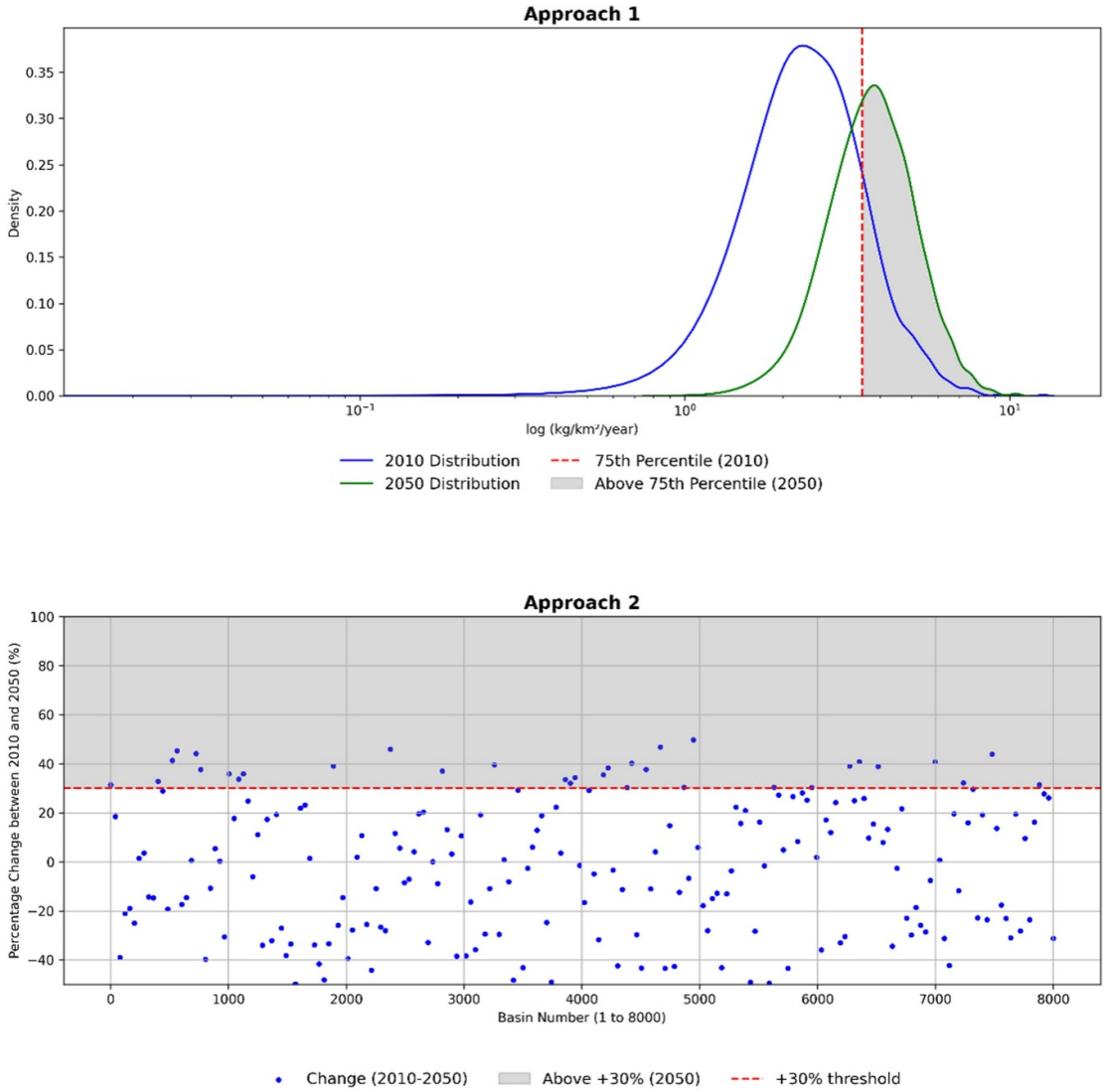

Figure 1. Hypothetical examples of the two approaches for hotspot definitions, including quantile-based (approach 1, top) and direction-based (approach 2, bottom). The quantile-based approach identifies sub-basins as pollution hotspots where 2050 pollutant exports exceed the 75th percentile of 2010 pollution levels. The shaded area highlights these hotspots. The direction-based approach (bottom) identifies sub-basins as pollution hotspots with ⩾30% increases in pollutant exports from rivers from 2010 to 2050. Blue dots represent the percentage change per sub-basin (hypothetically), with those above the threshold highlighted in the grey area. These two approaches aim to provide insights into future high-pollution areas (quantile-based) and those with rising pollutant loads (direction-based). *Source*: the approaches are applied to the model results from the MARINA-Multi model (see section 2 for details).

attention to prevent future pollution but may not be on policymakers' priority lists due to their low pollution levels. To analyse the drivers of these multi-pollutant hotspots, we classified sub-basin areas as low-income (LI), lower-middle-income (LMI), upper-middle-income (UMI), and HI based on the World Bank classification [49] (see details in SI C). We applied a fixed 2010 income classification for both 2010 and 2050 in our multi-pollutant analysis to ensure comparability and isolate environmental and policy effects from socio-economic changes (see discussion section).

Global change drivers: We evaluated pollution hotspots focusing on two main themes: urbanization and food production. The urbanization theme consists of four main drivers: (1) urban population, (2) sewage connection, (3) wastewater treatment, and (4) mismanaged waste that occurs largely in urban areas. The food production theme includes three main drivers, namely: (1) synthetic fertilizer use, (2) animal manure application on cropland, and (3) total population, which is used as a proxy for food demand. These seven drivers were selected for their influence on global pollution patterns. To assess future multi-pollutant hotspots, we outlined the assumptions underlying these drivers, which are modelled under the economy-driven SSP5-RCP8.5 scenario [11]. By 2050, the total population and urbanization rates are projected to continue to increase. The high economic growth in SSP5 might lead to

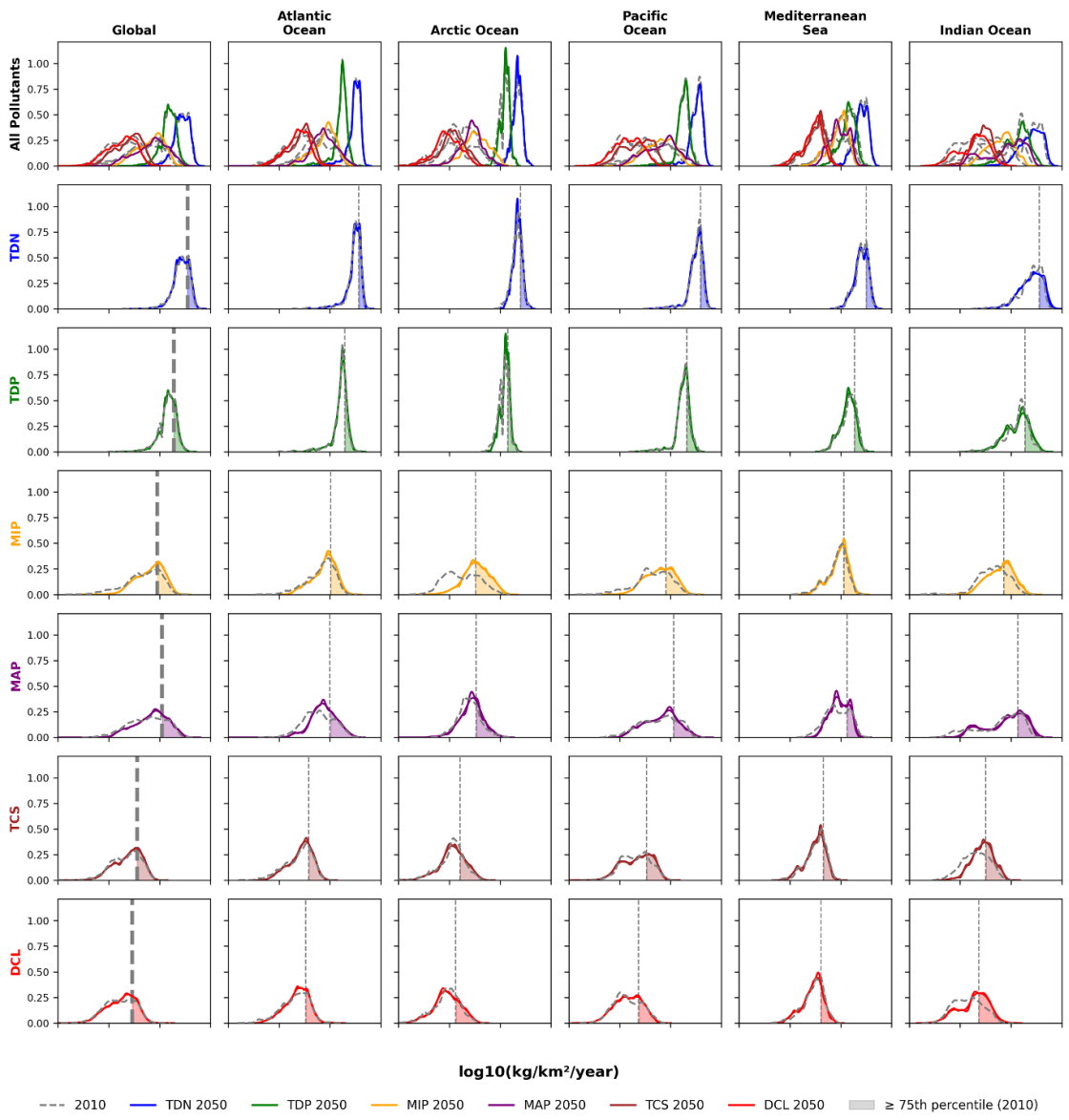

Figure 2. Probability distribution functions for river exports of pollutants (yields in log10 kg km^{-2} yr^{-1}) globally and for seas in 2010 and 2050. The *Y*-axis shows the frequency of sub-basins falling within a certain yield range on the *X*-axis. The curve indicates the distribution in river exports of pollutants including total dissolved nitrogen (TDN), total dissolved phosphorus (TDP), microplastic (MIP), macroplastic (MAP), triclosan (TCS), and diclofenac (DCL). Dashed lines are for 2010 and solid lines for 2050. The shaded area represents hotspots, defined using the quantile-based approach as river exports above the 75th percentile in 2010 (for each pollutant). The figure shows the river exports of pollutants that are averaged over five global climate models (GCMs). Results per GCM are provided in supplementary information annex G. *Source*: the MARINA-Multi model (see section 2 for details on the model and the definitions of hotspots).

expanded sewage connections, covering over two-thirds of the population. However, wastewater treatment efficiency is likely to see major improvements in Western Europe, North America, and East Asia. In contrast, South Asia, Sub-Saharan Africa, and South America may continue to face limitations in treatment capacity, especially for multiple pollutants. Additionally, mismanaged waste is projected to double globally, potentially widening regional inequalities in waste management. In food production, global trends suggest that agricultural intensification may continue, with increased synthetic fertilizer use by 54% for nitrogen (N) and 30% for phosphorus (P). Manure application is estimated to increase by 25% (N) and 12% (P) between 2010 and 2050, respectively. Further details for these projections are described in Micella *et al* [11].

Drivers vary in their values and units. To compare the drivers and ensure compatibility across sub-basins, we standardized the values to a 0–1 scale using the cumulative density function (CDF), following Vorosmarty *et al* [46]. First, each driver's original values (e.g. kg^{-1} yr^{-1} or rates from 0 to 1) were ranked (k), and sub-basins with zero values were excluded to focus on sub-basins with human activities. Next, the non-zero values were summed (N_{tot}), and the normalized D was calculated by dividing the

ranked driver's values by the sum (N_{tot}). By applying cumulative density functions, we reduced the influence of outliers and highlighted relative differences across sub-basins (see details in SI E). An illustrative example comparing original and normalized values (synthetic fertilizer use) is provided in SI figure E.8.

3. Results

3.1. Probability density functions (PDFs) for river exports of pollutants

For 2010 (reference year), PDFs differ among river exports of pollutants globally and across seas (figure 2). Globally, pollutant distributions are all skewed to the left (i.e. the mean is lower than the median), which implies that most sub-basins have relatively high river exports of pollutants. The distribution curves for river exports of pollutants by sea have sharp peaks exceeding 0.5 on the y-axis (except for the Indian Ocean) and are all skewed toward the left (except the Arctic Ocean) with modes ranging from 35.9–234.9 kg km^{-2} yr^{-1} for TDN and 1.5–7.4 kg km^{-2} yr^{-1} for TDP (figure 2, SI D). This implies that river exports of nutrients are generally high and show low variability among sub-basins worldwide (figure 2, SI D). Exceptions are found for river exports of chemicals and plastics, which have flatter curves (sd $>$ 1 for each sea), all below 0.5 on the y-axis (figure 2). For plastics, modes across seas range from 0.004–0.3 kg km^{-2} yr^{-1} for MIP and 0.01–0.8 kg km^{-2} yr^{-1} for MAP. For chemicals, modes range from 0.01 to 7.5 g km^{-2} yr^{-1} for DCL, and 0.06–2.1 g km^{-2} yr^{-1} for TCS (figure 2, SI D). This implies a higher variability in river exports of plastics and chemicals, in yields (skewness ranging from -0.83 to 1) and across sub-basins (sd $>$ 1) compared to nutrients.

For 2010, among the five classified seas and oceans (see SI B for classification), the Pacific and Atlantic Oceans generally have the highest modes across pollutants exported by rivers. For the Arctic Ocean, these modes are the lowest (figure 2, SI D). For the Mediterranean Sea, river exports of all pollutants generally show a more clustered distribution (lower sds). River exports of all pollutants into the Indian Ocean show more widely spread distributions (relatively higher sds). This also holds for the Atlantic Ocean, but only for nutrients, and for the Pacific Ocean for plastics and chemicals. For the Arctic Ocean, distributions of river exports of pollutants are skewed to the right, implying generally lower pollution yields. In contrast, river pollutant exports to other seas are mostly left-skewed, indicating generally higher pollution yields (with values clustering toward the right side of the distribution).

In 2050, the distribution curves for the river exports of pollutants are projected to become more clustered globally and across seas (figure 2). This implies a reduced variability in river exports of pollutants across sub-basins in 2050 compared to 2010. However, the distribution curves differ in their modes, skewness, and peak heights (figure 2, SI D). Globally, the modes for river exports of nutrients, MAP, and DCL are projected to be higher in the future, with average increases ranging from 3% to 120% by 2050. This suggests that sub-basins are expected to experience more pollution in 2050. In contrast, we project lower modes for MIP and TCS globally, with decreases of 32%–48%. However, the peak height of their distribution curves increases, with MIP rising by 19% and TCS by 27% between 2010 and 2050. In comparison, the peak height of the global distribution curves for nutrients is expected to decrease slightly by approximately 3% from 2010 to 2050. Asymmetries in the global distribution curves are projected to increase for MAP, DCL, and TCS, with skewness values increasing by 43%–126% by 2050. This results in more left-skewed distributions, reflecting a shift in pollution levels (yields in kg km^{-2} yr^{-1}) toward increased densities around higher values, rather than overall increases in the distribution curves between 2010 and 2050. In contrast, a more balanced distribution is projected for future river exports of nutrients and MIP compared to 2010, with skewness values decreasing by 21%–38% by 2050. This suggests reduced regional disparities between 2010 and 2050.

For the 2010–2050 period, among the five classified seas and oceans, more diverse changes in the distribution curves are projected, particularly for the modes and skewness (figure 2). For the Indian Ocean, the modes of river exports are projected to increase for most pollutants (except TCS) by 10%–220% from 2010 to 2050. For the Arctic Ocean and Mediterranean Sea (figure 2), the projected increases in the modes of pollutant exports by rivers are found for fewer pollutants. Specifically, for the Arctic Ocean, the modes of nutrients and MIP are projected to increase by 63%–320% between 2010 and 2050, whereas for the Mediterranean Sea, modes of TDP, MIP, and DCL are projected to increase by 4%–59%. In contrast, decreases in modes of river export of most pollutants are projected for the Atlantic Ocean (all, except for TDN: +244%) and the Pacific Ocean (all, except for MAP: +207%). By 2050, all seas are projected to show sharper and higher peaks in their distribution curves for most pollutants compared to 2010, with generally the most prominent changes for plastics and the least prominent changes for nutrients. Nonetheless, changes in their symmetry between 2010 and 2050 (figure 2, SI D) are projected to be more diverse, with the most prominent changes in river exports of MAP in the Atlantic Ocean and river exports of DCL in the Indian Ocean, both projected to become more left-skewed by 2050.

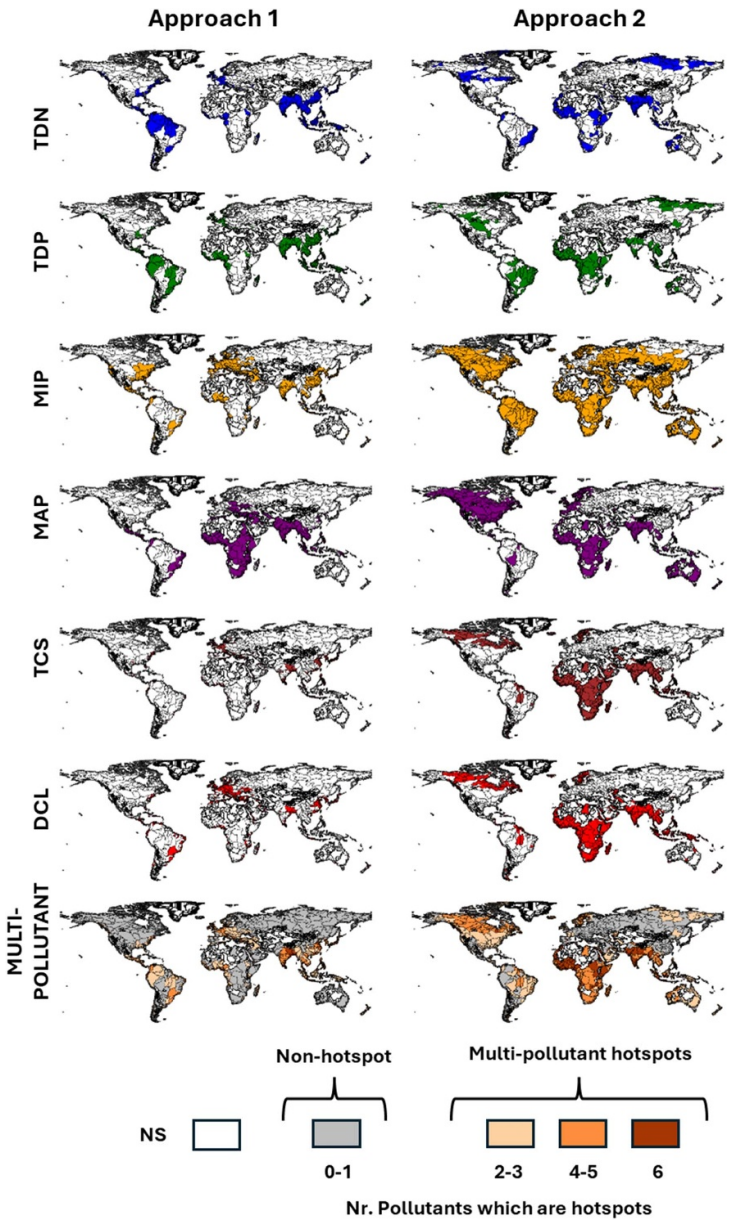

Figure 3. Sub-basins as single-pollutant and multi-pollutant hotspots in 2050 under an economy-driven scenario using two complementary approaches. Hotspots are determined for 8 890 sub-basins based on their projected river exports of six pollutants for 2010 and 2050 (kg km^{-2} yr^{-1}). The two approaches are quantile- and direction-based. In the quantile-based approach (approach 1, left panels), hotspots (coloured polygons) are defined as sub-basins that, in 2050, exceed the 75th percentile of the global distribution of pollutant levels in 2010. In the direction-based approach (approach 2, right panels), hotspots (coloured polygons) are defined as sub-basins with at least a 30% increase in pollutant levels in 2050 compared to 2010. Pollutants considered are total dissolved nitrogen (TDN), total dissolved phosphorus (TDP), microplastic (MIP), macroplastic (MAP), triclosan (TCS), and diclofenac (DCL). The multi-pollutant perspective shows sub-basins in which two or more single-pollutant hotspots overlap, forming multi-pollutant hotspots (bottom panels). NS stands for not studied, indicating some sub-basins that are not considered in this analysis (the white polygons). This is because they do not drain into the coastal waters (inland sub-basins) or are located in Greenland. *Source*: the MARINA-Multi model (see section 2 for details on the model, the scenario, and the definitions of hotspots).

3.2. Comparison of multi-pollutant hotspots between two approaches

We apply two complementary approaches: the quantile- (figure 3, approach 1) and the direction-based (figure 3, approach 2). Each approach provides a unique perspective on future pollution hotspots. The quantile-based approach highlights sub-basins with high pollution levels in 2050, which builds on high pollution in 2010 (exceeding the 75th percentile). In contrast, the direction-based approach identifies sub-basins where pollution is projected to increase rapidly (at least 30% by 2050), even if pollution levels were not yet high in 2010 (they did not exceed the 75th percentile). By using both approaches, we reveal two insights: (1) where pollution is expected to remain high (or persistent) in 2050 and/or (2) where pollution is projected to increase largely by 2050, resulting in emerging pollution hotspots.

For 2050, the hotspots of individual pollutants differ between the quantile- and direction-based approaches (figure 3, first six rows). Globally, the quantile-based approach suggests fewer hotspots in 2050. For example, 9%–30% of the total sub-basin areas worldwide are defined as hotspots depending on the pollutants (figure 3, left panels). In the direction-based approach, this is 25%–77% of the sub-basin areas, indicating that future hotspots are much more widespread worldwide (figure 3, right panels). For river exports of MIP, the spatial distribution of future pollution hotspots differs the most among the two approaches: 24% in the quantile-based and 77% in the direction-based worldwide. In contrast, for river exports of TDN, the differences between the two approaches seem to be the smallest compared to the other pollutants. The quantile-based approach suggests that future pollution hotspots mainly occur in Asia and Europe (except for MAP), whereas the direction-based approach suggests that pollution hotspots are largely located in Africa, Asia, and North America (figure 3). Globally, future multi-pollutant hotspots span nearly twice as much area under the direction-based approach (60%) compared to the quantile-based approach (32%) (figure 3, bottom panels). These two approaches yield different insights for Asia and Africa. In 2050, the quantile-based approach identifies multi-pollutant hotspots in Asia, covering 3% of the global sub-basin area, whereas the direction-based approach expands this coverage to 10% across with multi-pollutant hotspots in both Africa and Asia. This indicates that the spatial extent of these hotspots more than triples under the direction-based method.

For Asia, multi-pollutant hotspots are projected because of the high pollution levels in 2050 based on the quantile-based approach (figure 3, left panels). In this quantile-based approach, sub-basins with high pollution levels, which are persistent in 2050, are identified as hotspots. This also holds for Western European sub-basins. By 2050, river exports of nutrients are projected to contribute to pollution hotspots covering 20%–25% of sub-basin areas worldwide. These hotspots are mainly located in agricultural zones of Southern Asia, Western Europe, and South America. River exports of plastics are projected to contribute to pollution hotspots across 20%–40% of sub-basin areas worldwide that are mainly concentrated in densely populated coastal zones such as Southeast Asia, East Asia, and Europe. River exports of chemicals are projected to contribute to pollution hotspots in 15%–20% of sub-basin areas, particularly in the urban and industrial regions of South Asia, Southeast Asia, and Europe (figure 3, left panels). In this quantile-based approach, sub-basins with high yields in 2010 will likely remain pollution hotspots in 2050, even in areas where slight decreases are projected over time. The approach may underestimate future hotspots, especially in Africa, where pollution is projected to increase by 2050.

For Africa, multi-pollutant hotspots are projected because of high pollution increases by 2050 based on the direction-based approach (figure 3, right panels). In this direction-based approach, sub-basins with rapidly emerging pollution levels are identified as hotspots, even though their absolute pollution levels are not necessarily high. The direction-based approach suggests future multi-pollutant hotspots for many Asian and North American sub-basins, which is similar to the quantile-based approach. By 2050, river exports of nutrients are expected to contribute to pollution hotspots spanning 20%–25% of global sub-basin areas that are mainly located in agricultural regions such as South Asia, East Asia, the United States, Europe, and Central Africa. For plastics, future pollution hotspots are projected to cover at least 60% of global sub-basin areas for river exports of MIP and over 80% for river exports of MAP. These hotspots are primarily expected across Asia, Africa, and parts of Europe. Pollution hotspots for river exports of chemicals are projected to cover 15%–25% of sub-basin areas worldwide, which is similar to the quantile-based approach (figure 3, right panels).

By combining the quantile- and direction-based approaches, we can identify sub-basins where pollution is projected to be high in 2050 (>the 75th percentile) and increase (at least 30%) by 2050. This implies that the future pollution hotspots between the two approaches match. Figure 4 shows the spatial overlap and divergence between the two hotspot classifications, with four categories identifying persistent-only, emerging-only, overlapping, and non-hotspot areas. Our findings reveal that the two approaches consistently identify hotspots (persistent and emerging) in 12%–20% of the global sub-basin area for plastics and phosphorus, primarily located in Asia (figure 4). For other pollutants, this overlap is less than 5% on a global scale. Furthermore, 3%–20% of sub-basin areas globally already have high pollution levels but are projected to experience either relatively small increases (less than 30%) or even decreases in pollution levels by 2050 (Persistent-only in figure 4). This suggests that while future pollution remains a concern in these areas, its rate of increase will be relatively moderate by 2050. Most importantly, we find that 18%–50% of the sub-basin areas had relatively low pollution levels in 2010 but are projected to experience considerable increases (>30%) in pollution by 2050 (Emerging-only in figure 4). We classify these as emerging hotspots, defined by relative increases over time, regardless of absolute pollution levels or direct ecological risks. It is important to note that such increases can occur

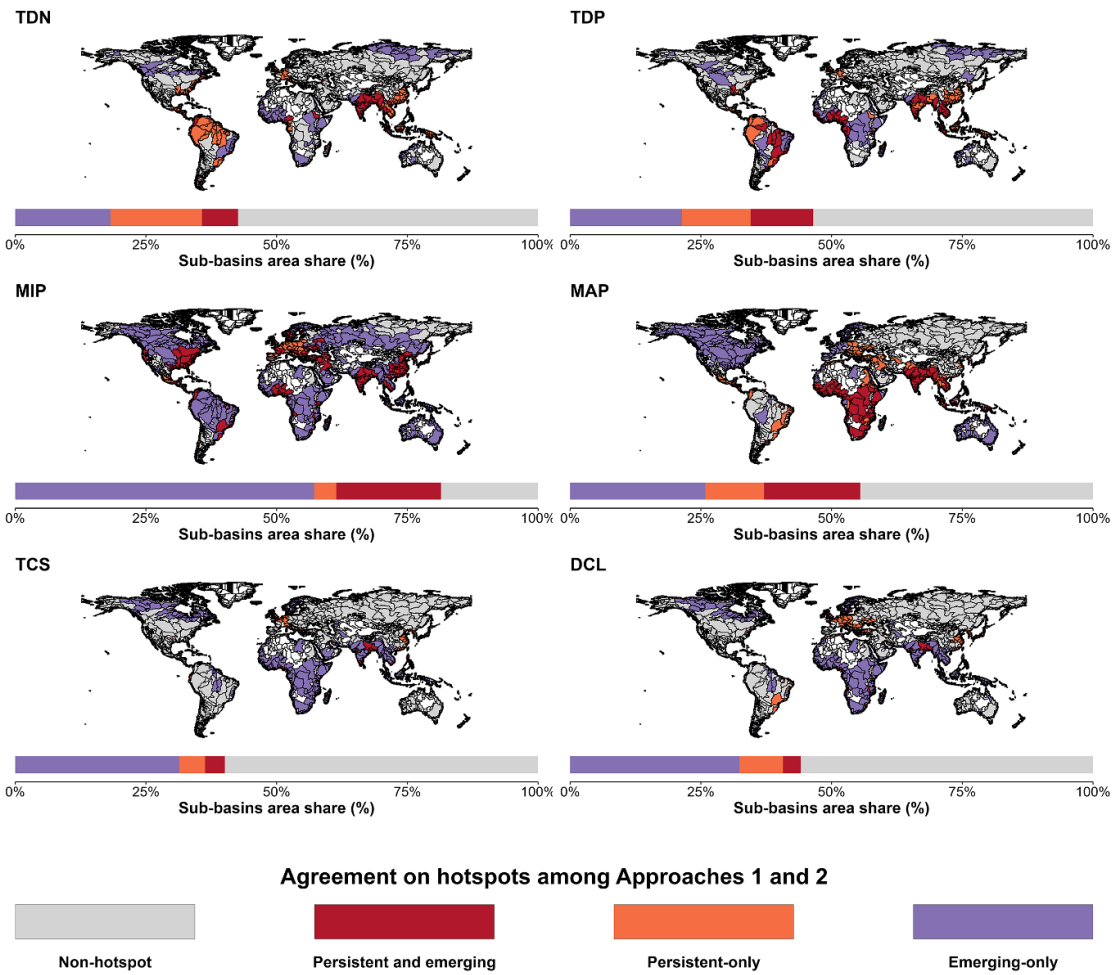

Figure 4. Agreements of pollution hotspots for river exports of six pollutants between the two approaches of this study. Hotspots were identified using a quantile-based approach, defining persistent hotspots as areas where river pollutant exports exceed the 75th percentile (approach 1), and a direction-based approach, identifying emerging hotspots as areas where exports are projected to increase by at least 30% between 2010 and 2050 (approach 2). The analysis covers total dissolved nitrogen (TDN), total dissolved phosphorus (TDP), microplastics (MIP), macroplastics (MAP), triclosan (TCS), and diclofenac (DCL), across 8890 sub-basins globally. Maps classify sub-basins into four categories: persistent-only hotspots (orange, identified solely by the quantile-based approach), emerging-only hotspots (purple, identified solely by the direction-based approach), persistent and emerging hotspots (dark red, where both approaches overlap), and non-hotspots (grey, flagged by neither approach). Horizontal bars indicate the global percentage of sub-basin areas in each category for each pollutant (%), illustrating spatial patterns of hotspot agreement and divergence. Some sub-basins (white polygons) were not considered in this analysis because they do not drain into the coastal waters (inland sub-basins) or are located in Greenland. *Source*: the MARINA-Multi model (see section 2 for details on the model, the scenario, and the definitions of hotspots).

in areas starting from low baseline levels and do not indicate ecological concern but rather give a warning signal of increasing pollution levels. Nonetheless, emerging hotspots are critical early warning signals, especially for pollutants like MIP, where over 50% of global sub-basin areas are projected to experience >30% increases by 2050 (figure 4).

Looking at regional patterns, sub-basins in Asia classify as hotspots under both approaches, covering areas ranging from 6% (DCL) to 28% (MIP). In contrast, sub-basins in Africa and Central and South America are more frequently identified as hotspots by the direction-based approach. In Africa, 40%–59% of the surface area falls into the emerging-only hotspot category, particularly for MIP (59%), TDN (41%), and TDP (43%). In Central and South America, emerging-only hotspots account for 17% (TCS) to 36% (MIP) of the area (figure I.1). This confirms that while persistent-only hotspots dominate in parts of Asia, emerging-only hotspots are substantially more prevalent in Africa and Latin America, supporting the added value of using both approaches. These results highlight the urgent need to address pollution not only in heavily contaminated sub-basins (persistent hotspots) but also in sub-basins where pollution is expected to increase rapidly, resulting in emerging pollution hotspots (e.g. many African sub-basins). Identifying these areas enables early warning and proactive intervention before pollution reaches critical ecological impacts. Therefore, in the following sections, we focus on direction-based

Figure 5. Proportions of populations across income levels and regions for hotspots and non-hotspots in 2050 under an economy-driven scenario (%). Results from sub-basins are aggregated to regions. Hotspot sub-basins are identified using the direction-based approach: at least a 30% increase in river export of pollutants between 2010 and 2050. Sub-basins are classified using income levels based on the World Bank's classification: low-income (LI), lower-middle-income (LMI), upper-middle-income (UMI), and high-income (HI). The bar charts categorize populations that are expected to live in the hotspot and non-hotspot sub-basins in 2050. Pollutants include total dissolved nitrogen (TDN), total dissolved phosphorus (TDP), microplastics (MIP), macroplastics (MAP), diclofenac (DCL), and triclosan (TCS). *Source*: the MARINA-Multi model (see section 2 for details on the model, scenario, income classifications, and hotspot definitions).

(emerging) hotspots to highlight regions where rising trends warrant attention, even if absolute levels remain rather moderate.

3.3. Uneven distribution worldwide: multi-pollutant hotspots and their drivers

Here, we further analyse multi-pollutant hotspots of the direction-based approach. We analyse them for sub-basins that are classified based on income levels: LI, LMI, UMI, and HI (see section 2). We start with the population in 2050 that is projected to live in areas of future multi-pollutant hotspots. Then, we analyse future urbanization and food production drivers for those multi-pollutant hotspots under different income levels. We compare hotspots with non-hotspots to identify differences and similarities in their drivers across income levels.

○ Population in future multi-pollutant hotspots under different income levels

In 2050, the total population living in multi-pollutant hotspots is projected to be unevenly distributed across HI and LI sub-basins (SI C). Globally, multi-pollutant hotspots are expected in LI sub-basins (LI and LMI). This implies that 75%–95% of the LI population worldwide (urban and rural) is projected to live in multi-pollutant hotspots, with at least half exposed to all six pollutants (figure 5).

HI sub-basins (HI and UMI) are largely located in Europe, North America, Central & South America, and Oceania. These regions are economically developed. For them, future multi-pollutant hotspots are mainly associated with two or three pollutants in which plastics often dominate (figure 5). By

2050, the HI population in European sub-basins is projected to reach 0.76 billion (SI C). In this group, 30% (MIP) and 68% (MAP) are expected to live in plastic-associated hotspots (figure 5). In North American HI sub-basins, the HI population is expected to reach 0.71 billion by 2050 (SI C), with at least 80% living in plastic-associated hotspots (MIP and MAP, figure 5). The Central & South American HI sub-basins expect to host 0.48 billion people in 2050 (SI C), of which at least 50% is expected to live in MIP- and nutrient-associated hotspots (figure 5).

LI sub-basins (LI and LMI) are largely located in Asia and Africa. Their future multi-pollutant hotspots are mainly associated with more than three pollutants (figure 5). Although these sub-basins cover 70% of Africa's sub-basin area and only 30% of Asia's (SI C), a much larger number of people are expected to live in the Asian sub-basins. By 2050, Asia's LI sub-basins, particularly in India and Southeast Asia, are projected to accommodate approximately 2.53 billion people (SI C). More than half of this population is expected to live in hotspots exposed to three to six pollutants, with plastics and chemicals being the most common (figure 5). In Africa, LI sub-basins are projected to host about 1.63 billion people (SI C), with nearly half living in areas affected by all six pollutants. Together, the LI sub-basins in Asia and Africa will account for the majority of the global LI population exposed to pollution.

○ **Urbanization and food production drivers under different income levels**

Here, we use the same classification of the sub-basins based on income levels (LI, LMI, UMI, and HI). To compare the drivers among them and the sub-basins, we ranked their values for 2050 from the lowest (excluding zeros) to the highest and then normalized them to obtain *D* scores that range from 0 (low) to 1 (high) (figure 6). Lower scores imply that sub-basins have relatively lower values for drivers compared to other sub-basins in the world. The opposite applies to higher scores. In other words, sub-basins with higher *D* scores are likely characterized by more intensive human activities compared to sub-basins with lower *D* scores (section 2, SI E).

For HI and UMI sub-basins, urbanization and food production activities are expected to be more intensive than those in LI and LMI regions in 2050. However, the differences in those activities between future hotspots and non-hotspots are less pronounced. This can be observed by looking at the median *D* scores (figure 6, black line). The *D* scores for synthetic fertilizer use (0.62 for hotspots and non-hotspots), sewage connections (0.63 for hotspots), and wastewater treatment removal fractions (0.78 for hotspots and non-hotspots) are higher in HI sub-basins compared to LI sub-basins in 2050 (figure 6). Animal manure application on cropland is, however, an exception. The *D* score for manure is slightly lower in HI areas (0.38 for hotspots) compared to LI sub-basins (0.54 for hotspots, figure 6).

For LI and LMI sub-basins, urbanization activities tend to vary between pollution hotspots and non-hotspots in 2050 (figure 6). For example, in LI sub-basins, the median *D* score for urban population density is higher for hotspot sub-basins (0.65) than for non-hotspot sub-basins (0.57) in 2050. This implies that more urbanization is expected in hotspots in the future. In contrast, in LMI sub-basins, the median *D* score for mismanaged plastic waste is high and similar between hotspots (0.84) and non-hotspots (0.81) sub-basins. Therefore, mismanaged waste is expected to contribute largely to MAP pollution in 2050. For hotspot sub-basins, the median *D* score is much lower for sewage connections (0.23) and wastewater treatment removal fractions (0.16) compared to non-hotspot sub-basins. This indicates that hotspot sub-basins are expected to have poorer sanitation infrastructure compared to non-hotspot sub-basins in 2050. For agricultural drivers such as manure application, the median *D* scores do not largely vary between hotspot and non-hotspot sub-basins. This implies that food production is expected to occur in both hotspots and non-hotspots in 2050.

Our findings indicate that numerous sub-basins in Africa and Asia are expected to become multi-pollutant hotspots (figures 3 and 4). For African sub-basins, this is based on the direction-based approach, while for many Asian sub-basins, this is based on both quantile- and direction-based approaches (see SI I.1). Despite this shared classification as LI sub-basins, the underlying pollution drivers differ between regions for the year 2050. In LI African sub-basins, this trend is linked to rising levels of mismanaged plastic waste and limited wastewater treatment, both of which are expected to contribute to increased pollutant loads in freshwater systems (SI F). In comparison, LI Asian sub-basins are expected to have lower levels of mismanaged waste by 2050. However, synthetic fertilizer application rates in these areas are expected to remain above those in Africa and the global average, making them key contributors to future nutrient pollution, particularly in countries such as India (SI F).

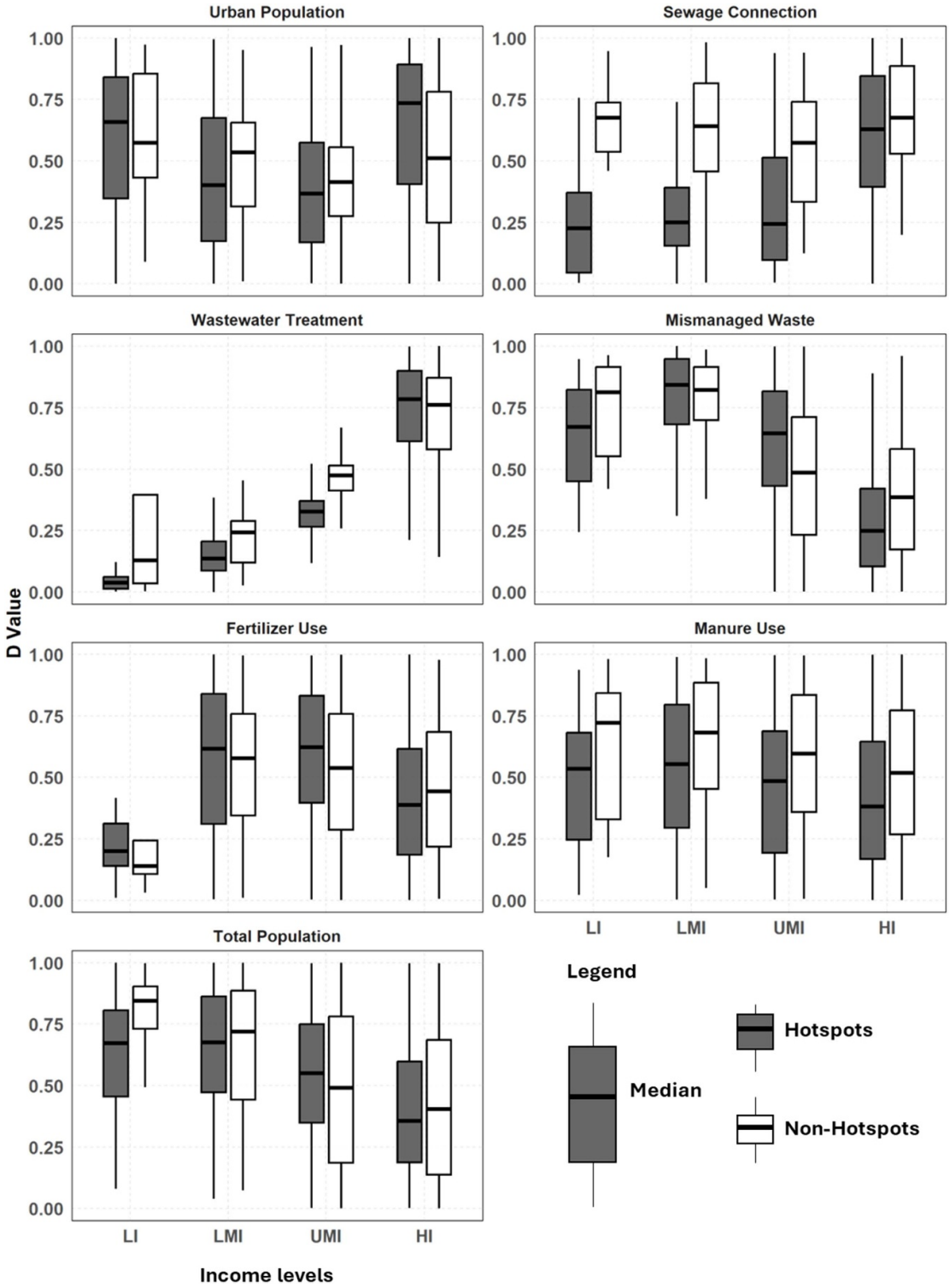

Figure 6. Box plots illustrating the spatially normalized distributions of seven drivers, for urbanization and food production, across income levels for 8890 sub-basins for the year 2050 (*D* values, 0–1). Sub-basins are classified using income levels based on the World Bank's classification: low-income (LI), lower-middle-income (LMI), upper-middle-income (UMI) and high-income (HI). Sub-basins are defined as hotspots (dark grey, being hotspots for more than two pollutants) or non-hotspots (white) using a direction-based approach: a ⩾30% increase in river export of pollutants between 2010 and 2050. To compare drivers among sub-basins, their values are ranked from the lowest (excluding zeros) to the highest and then are normalized to the *D* scores, ranging from 0 (low) to 1 (high). The seven pollution drivers are divided into urbanization (four drivers) and food production (three drivers). The urbanization theme consists of urban population, sewage connection, wastewater treatment, and mismanaged waste that occurs largely in urban areas. The food production theme consists of (synthetic) fertilizer use, manure use (animal manure application on cropland), and total population as a proxy for food demand. The box plot shows results for sub-basins considering statistical summaries, with black lines indicating median values. *Source*: the MARINA-Multi model (see section 2 for details on the model, income classifications, hotspot definitions, and the normalization approach).

4. Discussion

4.1. Model evaluation

The MARINA-Multi model is part of the wide model family with extensive evaluations of their approaches across time, scales [50] and across different spatial domains. Our model was evaluated through a building trust approach [51], including validation against available monitoring data, sensitivity analysis, comparisons with other literature, and expert knowledge [29]. For example, it was evaluated globally, as well as for China [28] and for Europe [52]. Validation results on a global scale showed a reasonable comparison between modelled values and available observations at the river mouths for nutrients, MAP and MIP [29]. Sensitivity analyses were performed to evaluate the robustness of the model's results. Wang *et al* [26] found that nutrient simulations in China were sensitive to changes in river discharge and manure inputs. Globally, Micella *et al* [29] tested the sensitivity of multi-pollutant hotspots and compared their spatial variability with other models. Micella *et al* [11] found that future pollution was mostly sensitive to socio-economic changes. Comparisons with other models showed that MARINA-Multi results for the river exports of nutrients, plastics, and DCL globally were comparable to the results of other models, but lower for TCS [29]. Furthermore, this study applies a sub-basin spatial resolution, consistent with the MARINA modelling framework [1]. While point source pollution can exhibit high spatial variability within sub-basins, this scale is less limiting for diffuse sources. The sub-basin approach balances data availability and global consistency and has been widely used in global multi-pollutant assessments [9].

In this study, we used hydrology per GCM (five in total) as input to MARINA-Multi and ran the model yearly to simulate river exports of pollutants per sub-basin and GCM. The use of annual-scale data is consistent with many global assessments [39, 53], enabling comparability across pollutants and regions. While seasonal variability plays a critical role in local pollution dynamics, especially for impact assessments, addressing intra-annual patterns remains an important direction for future research in multi-pollutant assessments. We then averaged the annual river exports of pollutants over the five GCMs (see section 2.1). Thus, uncertainties may arise from climate forcings that underpinned the VIC model's hydrological simulations. Bak *et al* [33] compared the runs of MARINA-Multi between the five GCMs to assess potential uncertainties associated with climate-driven hydrological changes. This comparison showed relatively higher uncertainties in (highly) arid areas such as parts of Africa and Australia than in other parts of the world. In general, river exports of nutrients differ more among the five GCM runs than do river exports of plastics and chemicals (see Bak *et al* [33] for details).

4.2. Methodological insights

o **Insights from hotspot approaches**

Pollution hotspots can be defined in several ways [54]. This study presented two complementary approaches: the quantile- and direction-based (figure 3). Integrating both approaches contributes to a comprehensive analysis of the pollution hotspots (figure 4).

The quantile-based approach provides a standardized benchmark for comparing pollution levels across 8 890 sub-basins. A flexible threshold, such as the 75th percentile, allows for broad application, though alternative thresholds (e.g. the 90th and 50th) have been explored [29]. This approach ensures comparability across sub-basins [26, 28, 43, 44]. It is transparent and easy to use. However, a fixed threshold limits adaptability, potentially overlooking emerging pollution in the future, particularly in low-pollution areas of today (e.g. African sub-basins). Yet, the quantile-based approach is strong in identifying persistent hotspots (sub-basins exceeding the 75th percentile, figures 3 and 4). For example, this method performs well for sub-basins with narrow distributions of river exports, especially for pollutants like TDN and TDP (see figure 2). In contrast, it may underrepresent key hotspots for pollutants with wider river export distributions, such as MAP and TCS (see figure 2).

The direction-based approach is used to analyse pollution changes within individual sub-basins by comparing the values from 2010 to 2050 [1, 27, 45]. This approach does not rely on absolute pollution levels or their global distributions, as the quantile-based approach (figure 3). The direction-based approach can effectively identify future emerging hotspots, even in today's low-pollution regions. This could serve as a warning signal for those regions to be proactive and adapt their current environmental strategies to avoid future pollution. On the other hand, this approach may overestimate the severity of future hotspots. For example, sub-basins with exceptionally low pollution levels in 2010 might be projected to increase by at least 30% by 2050. In this case, the direction-based approach would define those sub-basins as hotspots. Their increased pollution levels in 2050 may, however, still be low enough not

to cause environmental impacts. Nevertheless, we argue that projected future increases should be considered a signal to act, not to wait until severe pollution and its environmental impacts occur in the 21st century.

Our two thresholds (75th percentile and 30% increase between 2010–2050) are arbitrary but supported by other existing studies. Several studies used the statistical thresholds (75th percentile) to identify pollution hotspots [29]. Other studies used a 30% increase in pollution levels to quantify the extent to which pollution is expected to increase in the future [1]. Existing studies also used other statistical thresholds [28]. To better understand the influence of our threshold choices on the main conclusions, we conducted a sensitivity analysis (see the SI figures G.1 and G.2). We assessed the sensitivity of the 55th and 95th percentiles on the hotspots, as well as 10% and 50% increases between 2010 and 2050. We compared the hotspots found with the sensitivity thresholds with our original hotspots. Results show that the overall spatial patterns, main conclusions, and their policy implications remain consistent, which reinforces the robustness of our framework. Finally, to test the robustness of our findings, we also ran the model under the SSP1–RCP2.6 scenario (see supplementary information figures H.1–H.3). While the magnitude of change varies, the overall spatial distribution of identified hotspots remains consistent, confirming the robustness of our conclusions.

Combining both approaches provides a comprehensive perspective on pollution hotspots, extending beyond their individual advantages (figure 4). The quantile-based approach identifies sub-basins with persistently high pollution levels in the absence of effective environmental action. This holds for India, China, and Central Africa for phosphorus, and in India and Africa for plastics. The direction-based approach highlights emerging hotspots, where pollution is projected to rise rapidly by 2050, particularly in the African and Indian sub-basins across most pollutants. Integrating the insights of both approaches provides a comprehensive framework to learn from both persistent and emerging pollution hotspots. This framework offers a powerful tool for multi-pollutant assessments and short- and long-term environmental planning.

Finally, we defined multi-pollutant hotspots as areas where at least two pollutants exceed their thresholds, which we set as either the 75th percentile, a 30% increase from 2010 to 2050, or both. In this approach, all pollutants are treated equally because our goal was not to assess their individual or combined impacts. Instead, we focused on identifying sub-basins with potential multi-pollutant issues globally, regardless of specific pollutant effects or ecological risks. We suggest that future analyses focused on pollutant impacts, such as for pharmaceuticals or MIP, should apply pollutant-specific weights based on toxicity [55] or persistence [56]. Another possibility is to add expert-based weights [46].

○ **Economic levels and normalized drivers**

We classify sub-basins for 2010 and 2050 by the income levels of 2010 [49] (mostly based on GDP, see SI C). The year 2010, also serves as the baseline year for our assessment. Although projected GDP growth is included in our scenario analysis, income classifications for 2050 remain fixed at 2010 levels. On the one hand, the consistency in the income classification between 2010 and 2050 allows us to make hotspot comparisons across sub-basins and excludes uncertainties in future GDP projections that could influence the classification. On the other hand, our classification may not fully reflect future changes in economic developments. This is because income levels may grow rapidly in some sub-basins while the growth may stagnate in others. Moreover, the income class thresholds may be higher in 2050 than in 2010, affecting the definitions of LI, LMI, UMI, and HI. While this static approach supports comparability, it may overlook future shifts such as economic advancement in currently LI regions. Dynamic classifications aligned with SSP-based income projections (projected GNI, e.g. [57]) could better capture such transitions, though they would introduce additional uncertainty and model complexity. Exploring alternative classification systems that account for the temporal changes in income levels can provide additional insights [58]. Moreover, LI sub-basins are expected to experience more pollution (e.g. figures 2 and 3). Additionally, our model does not fully account for unregulated pollution sources (such as improper sanitation facilities or informal economic activities) that are often more common in LI areas [59]. Given their current low economic development and the projected increase in pollution, water pollution control may be challenging.

This study relies on diverse global datasets that vary in resolution, completeness, and methodological approaches, particularly regarding point versus diffuse source estimations (see supplementary table A.1). To consistently analyse the drivers of water pollution, we normalized their values using a cumulative density function (CDF) [46]. This approach standardizes all studied drivers into a consistent numerical scale (0–1). This enabled us to make cross-sub-basin and cross-driver comparisons while mitigating data inconsistencies. While the CDF normalization reduces some comparability issues, uncertainties

remain, especially due to data aggregation to sub-basins and reliance on modelled or proxy data for certain drivers (e.g. sewage connection, mismanaged plastic waste). Nevertheless, all our data is based on published materials and checked for quality in earlier studies [11]. We believe that uncertainties associated with data sources do not change the main conclusions of our study.

By linking multi-pollutant hotspots (figures 3 and 4) with normalized drivers (figure 6), we identified the key pollution drivers. This approach allows us to relatively rank the importance of drivers in shaping pollution patterns. However, we cannot attribute a specific percentage of pollution to any single driver. What we can assess is the relative contribution of a given driver across different sub-basins. This information helps us better understand how future hotspots in South Asia, Sub-Saharan Africa, and Latin America (figures 3 and 4) align with low wastewater treatment efficiency and low sewage connections (figure 6). For example, LI sub-basins in Sub-Saharan Africa face high population pressure (medians >0.6) alongside the lowest relative sewage connection and wastewater treatment levels (both <0.3) (SI figure F). In Asia, many sub-basins have better treatment (around 0.4–0.5), which may help reduce pollution. However, problems such as mismanaged waste and excessive fertilizer use still lead to pollution. Similarly, mismanaged waste in LI sub-basins corresponds to pollution hotspots, emphasizing the need for improved waste management policies. However, this approach has its limitations as the 0–1 scale reduces the impact of extreme values. The CDF normalization smooths absolute values, potentially obscuring key interactions, and remains sensitive to data accuracy (details are in our previous studies [11]). Nevertheless, we believe that our approach provides valuable insights for prioritizing drivers that require more attention in water pollution control.

4.3. Implications for pollution control and future outcomes

This study shows how hotspots for multiple pollutants may shift across income groups and regions, identifying where land-based pollution is expected to change and how those changes increase the amount carried by rivers to coastal waters. Examining what drives these multi-pollutant hotspots points out the sub-basins that will have the greatest impact on future coastal water quality. The findings provide the information needed to understand land-based pressures on coastal areas, supporting coordinated local and global efforts to reduce multiple pollutants simultaneously at their sources. In our analysis, we focus on pollution hotspots across HI (HI and UMI) and LI (LI and LMI) sub-basins (figures 5 and 6).

HI sub-basins are largely located in developed regions such as Europe, North America, and Oceania. Multiple contaminants already pollute these sub-basins, but future increases in pollution levels are expected to be limited for most pollutants (figure 3). An exception is plastic, which is projected to increase largely by 2050. This is mainly associated with rising per capita plastic consumption and insufficient waste management (land-based sources). To address these challenges, HI basins are advised to focus on adaptation strategies to address current nutrient and chemical pollution and prevent future plastic pollution [60]. Such strategies need to take an integrated approach that targets the drivers and hotspots highlighted in our results. Advanced technologies [61], waste-to-energy options, such as plastic incineration [62], or ozonation and activated carbon can potentially reduce inputs in rapidly urbanizing sub-basins [63]. These can be complemented by policy initiatives to enhance societal awareness of plastic issues. Circular-economy instruments, including extended producer responsibility, bans on single-use plastics, and recycling incentives, directly act on the drivers of emissions in this study [64, 65]. Still, without stronger regulation and better institutional coordination, shifting consumption patterns might be challenging, especially in regions where plastic demand is set to grow fastest [66]. Despite ambitious reduction targets, recycling infrastructure in many HI regions remains insufficient, and meaningful progress will require sustained investment, innovation, and knowledge exchange [67].

LI sub-basins are projected to experience multi-pollutant hotspots (figures 3–5) due to ongoing urbanization and intensified agriculture (figure 6). These sub-basins are largely located in Asian and African regions and have relatively lower economic development. This calls for cost-effective strategies to reduce future pollution in both regions [68]. Furthermore, many Asian and African sub-basins drain into the coastal waters of the Indian Ocean, complicating pollution control efforts. This underscores the need for greater coordination between the two regions to manage pollution.

In Asia, many sub-basins located in India and Southeast Asia are identified as persistent multi-pollutant hotspots by 2050. This means they are polluted today and will continue to contribute to future pollution, mainly due to nutrient runoff from agriculture and plastic waste (figures 3–6). Addressing these pressures requires interventions that act directly on the dominant drivers identified in our results. Hotspots linked to nutrient pollution, largely driven by agricultural sources, will require food-system measures that prevent trade-offs among crop and livestock production, water quality, and different sustainability objectives [69, 70]. In this context, improving fertilizer efficiency [71] and transitioning from

synthetic fertilizers to alternatives, such as bio-based options, could reduce future pollution by avoiding soil over-fertilization. National examples, such as China, have already implemented policies to reduce synthetic fertilizer use and promote manure recycling in croplands [72], which was shown to be cost-effective for reducing eutrophication [73] and water scarcity [68]. Urbanized basins, where wastewater and plastic loads grow fastest, require aligned interventions. Improving wastewater treatment for multiple pollutants could be costly. Therefore, it is recommended to first strengthen the primary treatment infrastructure to reduce MIP [74]. Building on this, effective secondary treatment can lower chemical and nutrient pollution in effluents [75, 76]. Where pressures remain high, upgrading treatment to tertiary technologies is costly, but could still be considered for further pollution reduction [77]. Effective waste collection practices can be incentivized through targeted policies and stakeholder involvement [78, 79], including subsidies to prevent pollution and enhance waste management efficiency [80]. All together, these measures target the specific pathways through which the identified sub-basins will drive future pollution trends.

In contrast, many African sub-basins are identified as emerging multi-pollutant hotspots in 2050. This means that they are not yet largely polluted, but their pollution levels are expected to increase rapidly in the future (figures 3 and 4). Thus, prioritizing proactive and cost-effective solutions is essential to mitigate future water pollution, especially when multiple pollutants arise from both agricultural and urban sources. In agriculture, practices such as crop rotation, intercropping, and agroforestry reduce nutrient leaching by improving soil conditions and limiting runoff [81]. Nature-based solutions, such as wetlands and riparian buffers, further slow and filter polluted flows before they enter coastal waters [82]. Using biosolids and recycled manure can reduce reliance on synthetic fertilizers [83], but biosolids must be screened for plastics and chemicals [84], and manure reuse is often limited by transport and institutional constraints [83, 85]. In urban areas, as of 2010, over half of Africa's population lacked proper sanitation and relied mainly on pit latrines [35]. In some African sub-basins, managing faecal sludge remains a major challenge [86]. Even where sewage systems exist, they are often inadequate, with secondary and tertiary treatments rarely implemented due to financial and infrastructure constraints [87, 88]. Enhancing wastewater treatment could greatly reduce pollution from nutrients [35], plastics [89], and chemicals [63]. Selecting appropriate treatment methods should consider five key factors: economic viability, environmental impact, technical feasibility, social acceptance, and effluent water quality [90]. Finally, implementing these strategies for agricultural and urban areas can be particularly challenging in many Sub-Saharan African countries, where environmental policies remain underdeveloped [85]. Thus, there is a need to enhance long-term environmental commitment through policy interventions [91], subsidies [92], and community engagement [93]. This could facilitate better waste management [94], the implementation of nature-based solutions [95], and the creation of initiatives to reduce plastic use while generating economic opportunities [64]. Improving wastewater treatment is costly, but essential, to mitigate pollution from point sources.

Our analysis identifies future hotspots for multiple pollutants and regions likely to face increased pressures from nutrients, plastics, and chemicals. By distinguishing between emerging and persistent hotspots, the most effective interventions are recommended for water systems. Connecting these hotspots to country income groups also indicates which responses might be potentially feasible. Without addressing land-based activities in these hotspot areas, progress towards achieving SDGs 6, 12, and 14 will be largely challenged. Building on these findings, it is clear that effective responses require not only technical interventions but also robust institutional frameworks and international cooperation [72]. Differences in law enforcement, investments in water infrastructure, and governance mechanisms can either mitigate or exacerbate pollution pressures. For instance, sub-basins with strong institutional coordination (e.g. the Mekong River Commission or river basin organizations in Europe) may be better able to manage pollution even under rising pressures. HI countries should focus on stricter plastic waste regulations and technological advancements, leveraging SDG 9 (industry, innovation, and infrastructure) and SDG 12 (responsible production and consumption) to reduce trade-offs with SDG 14 (life below water) [7]. In contrast, LI regions need targeted investments in sewage treatment, sustainable agriculture, and capacity-building, aligning with SDG 6 (clean water and sanitation), SDG 2 (zero hunger), and SDG 8 (economic growth). A balanced mix of affordable, economically feasible, and societally acceptable strategies is key to addressing current and future water pollution. Furthermore, future research should examine the impact of water pollution on healthcare costs [96], economic growth [97, 98], and social fragmentation [23, 99] to support evidence-based policymaking.

5. Conclusions

This study identifies future multi-pollutant hotspots of coastal waters and analyses their spatial distribution patterns associated with socio-economic drivers across global income levels. Future multi-pollutant hotspots of coastal waters are projected to be unevenly distributed worldwide, reflecting disparities among income groups. For Asia, multi-pollutant hotspots are projected due to high pollution levels in 2050. Many Asian coastal waters, already polluted in 2010, will continue to experience high levels of pollution from river exports of multiple pollutants, reinforcing existing pollution patterns. For Africa, future multi-pollutant hotspots are projected due to rapid increases in pollution levels by 2050, driven primarily by rapid population growth and poor waste management. In many African sub-basins, pollution levels are expected to rise sharply between 2010 and 2050, creating emerging multi-pollutant hotspots in 2050. Rapid urbanization is projected to drive future pollution hotspots with plastics in HI basins. In regions such as Europe, North America, and Oceania, plastic pollution is expected to remain a dominant issue, despite stronger environmental regulations and wastewater treatment systems. In LI basins, more than 75% of the population is projected to live in multi-pollutant hotspots by 2050. This is particularly evident in parts of Africa and South Asia.

These findings emphasize the urgent need to address income-based disparities in water pollution control and to support equitable and sustainable water management worldwide. A multi-pollutant approach is essential to mitigating these inequalities, particularly in low- and middle-income regions where resource allocation and management systems remain inadequate. To effectively tackle these challenges, globally coordinated efforts should prioritize region-specific solutions that align with local socio-economic and environmental conditions. The insights from this study can inform policies to achieve SDG 6 (clean water for all) and SDG 14 (life below water), promoting equitable access to clean water and strengthening resilience against future coastal water pollution.

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Data availability statement

The data that support the findings of this study will be openly available at the following URL/DOI: https://doi.org/10.17026/PT/WVRTGX [100].

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Conflict of interest

The authors declare that they have no competing interests.

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