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**Model inter-comparison design for large-scale water quality models**

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## 17 **Abstract**

18 Several model inter-comparison projects (MIPs) have been carried out recently by the climate,  
19 hydrological, agricultural and other modelling communities to quantify modelling uncertainties  
20 and improve modelling systems. Here we focus on MIP design for large-scale water quality models.  
21 Water quality MIPs can be useful to improve our understanding of pollution problems and facilitate  
22 the development of harmonized ~~data sets~~estimates of current and future water quality. This can  
23 provide new opportunities for assessing robustness in estimates of water quality hotspots and  
24 trends, improve understanding of processes, pollution sources, water quality model uncertainties,  
25 and to identify priorities for water quality data collection and monitoring. Water quality MIP design  
26 should harmonize relevant model input datasets, use consistent spatial/temporal domains and  
27 resolutions, and similar output variables to improve understanding of water quality modelling  
28 uncertainties and provide harmonized water quality data that suit the needs of decision makers and  
29 other users.

## 31 **Highlights**

- 32 • Model inter-comparison projects (MIPs) can identify robustness of-water quality hotspots  
33 and trends
- 34 • Water quality MIPs can improve understanding of pollution causes and model  
35 uncertainties
- 36 • MIP design should focus on using consistent input datasets and harmonize output variables,  
37 and spatial ~~and~~ temporal resolutions.
- 38 • MIPs of lumped models should focus on pollutant loadings at river basin outlets
- 39 • MIPs of grid-based models can compare spatial water quality heterogeneity within basins.

40

41 **1. Introduction**

42 In the last decade, there has been a strong focus on global and regional model inter-comparison  
43 projects (MIPs), ~~which in various research fields, including climate, hydrology (water quantity)~~  
44 ~~and agriculture (crop) modelling, have been used to contribute to a comprehensive and consistent~~  
45 ~~picture of model-derived insights in several fields, including climate, hydrology (water quantity)~~  
46 ~~and agriculture (crop) modelling.~~ The concept of MIP offers a framework to consistently evaluate  
47 and compare models, and associated model input, structural, and parameter uncertainty under  
48 different objectives (e.g. climate variability and change, model performance, human impacts and  
49 developments). Some of the most representative global MIPs include the Coupled Model Inter-  
50 comparison Project (CMIP) [1], the Agricultural Model Inter-comparison Project (AgMIP) [2],  
51 WATCH Water Model Inter-comparison Project (WaterMIP) [3,4] and the Inter-Sectoral Impact  
52 Model Inter-comparison Project (ISIMIP) [5]. These MIPs were mainly designed to better  
53 understand past, present and future climate changes and associated impacts on respective sectors  
54 (e.g. hydrology, agriculture, biomes, energy). One of the important goals of MIPs is to make the  
55 multi-model output publically available in a standardized format (e.g. netCDF).

56  
57 While there has been a significant amount of research and publications on MIPs and multi-model  
58 assessments for water availability, limited multi-model assessments for large-scale water quality  
59 studies exist [6,7]. Water quality problems exist in many parts of the world [8,9] and these issues  
60 may intensify due to climate change and socio-economic developments [10]. Robust estimates of  
61 current and future changes in water quality are needed to achieve sustainable management of clean  
62 accessible water for all, as required by the Sustainable Development Goal for clean water and  
63 sanitation (SDG 6) for 2030.

64

65 A large-scale water quality model is defined here as a model capable of simulating one or more  
66 water quality variables (pollutants) on a scale that exceeds the size of a single river basin-, which  
67 we define as the upstream land surface area contributing to the streamflow at the basin outlet (river  
68 mouth). Some examples of large-scale nutrient models are Global *NEWS-2* [11,12], SPARROW  
69 [13], IMAGE-GNM [14,15], HYPE [16] and MARINA [17]. In addition, large-scale water quality  
70 models including nutrients, salinity (e.g. total dissolved solids (TDS)) and organic pollution  
71 (biochemical oxygen demand (BOD)) have been developed, such as WaterGAP-WorldQual  
72 [18,19] and GWAVA-WQ [20,21].

73  
74 Development of large-scale nutrient models started in the 1990s, and since 2010 there has been a  
75 strong growth in the number of large-scale models for other pollutants too (Figure 1). For instance,  
76 global models have been recently developed for river water temperature [22-24], river water  
77 organic pollution [25], micro-organisms [26-28], chemicals [29], plastics [30-32], nanomaterials  
78 [33] and pesticides (insecticides) [34]. Most of the large-scale water quality models are spatially-  
79 explicit (commonly grid-based) and dynamic (i.e. account for temporal variability). The recent  
80 strong growth in the number of large-scale water quality models increases opportunities for  
81 comparing results from various models per water quality variable.

82 **[Fig 1]**

83  
84 In this paper, we review work published on model inter-comparison of large-scale water quality  
85 models, discuss reasons to move forward on water quality MIPs and give suggestions for future  
86 directions on water quality MIP design. We first discuss the lessons learnt from previous MIPs in  
87 other sectors (climate, water) (Section 2.1) and from previous large-scale water quality model inter-  
88 comparison studies (Section 2.2). We then consider opportunities (Section 3.1), challenges and

89 recommendations (Section 3.2) for design of water quality MIPs. We conclude by summarizing  
90 our main findings and examining how water quality MIPs could be designed to provide consistent,  
91 harmonized water quality model output datasets, which are more useful for policy makers and other  
92 users (Section 4).

93

94

## 95 **2. Previous large-scale model inter-comparison studies**

### 96 **2.1 Lessons learnt from MIPs in other sectors**

97 In ISIMIP, modelling protocols have been developed with an international network of climate-  
98 impact modellers to contribute to a comprehensive and consistent picture of the world's impacts  
99 under different climate-change scenarios across affected sectors (e.g. water, agriculture, energy,  
100 forestry, marine ecosystems) and spatial scales [35,36]. Overall, the focus of MIPs and associated  
101 concepts and modelling protocols is currently on understanding how model predictions vary across  
102 different sectors and different climate change scenarios. Within CMIP, the aim is to discover why  
103 different climate and earth system models provide different outputs despite receiving similar model  
104 input and identifying aspects of the simulations in which "consensus" in climate model projections  
105 or common problematic features exist [37]. To better understand the model spread and to reduce  
106 the associated uncertainties, a comparison of model performance and the sensitivity of the models  
107 to different warming rates may need to be studied further [38,39]. The consistent modelling  
108 framework of ISIMIP and CMIP using common input datasets and output variables has generated  
109 important datasets used by a broad research community and policy makers.

110

### 111 **2.2 Previous water quality MIPs**

112 Compared to other sectors (climate, water availability, agriculture) fewer MIP studies or multi-  
113 model assessments exist for water quality. Previous MIP studies for large-scale water quality have  
114 mainly focussed on nutrients. Comparisons of model results between different nitrogen (N) export  
115 models have been made, amongst others, at global scale [7], for Chinese basins [40], for the United  
116 States [6] and for selected sub-basins [e.g. 41,42]. These analyses have overall found fairly  
117 consistent loading predictions between similarly scaled models, despite varying levels of model  
118 complexity and differences in input data sources. The focus of most previous nutrient MIPs has  
119 been on comparing nutrient loads (e.g. kg N y<sup>-1</sup>) with less attention on source apportionment. An  
120 exception is McCrackin et al. [6], where comparing results of SPARROW and Global *NEWS-2* for  
121 the United States showed that for several regions similar N sources were identified by both models.

122  
123 A model inter-comparison has also been published for global river water temperatures [43] using  
124 global grid-based (0.5°) simulations of the water temperature modules of [the global hydrological](#)  
125 [models of](#) PCR-GLOBWB [23], VIC-RBM [24,44], and WaterGAP-WorldQual [22]. All three  
126 models were run using consistent model input for climate forcing, land mask, basin delineation and  
127 river flow direction (routing network). The three river water temperature modules show similar  
128 spatial patterns of water temperature [43] and identified similar regions with highest water  
129 temperature increase under climate change. However, the magnitude of water temperature changes  
130 varied, and this was mainly attributed to different representations of impacts of hydrological change  
131 and snowmelt inputs/ice cover processes [43].

132  
133 These previous nutrient/water temperature model inter-comparison studies have shown the  
134 importance of evaluating the performance of water quality models and highlighted the need of  
135 common input data to provide consistent water quality model output for comparison [41,43,45].

136

### 137 **3. Opportunities, challenges and recommendations for design of water quality MIPs**

#### 138 3.1. Opportunities to move forward on water quality MIPs

139 Comparing water quality model results can lend credibility to water quality simulations and  
140 identify areas for future model improvement [6]. Water quality MIPs could facilitate the  
141 development of harmonised model output data sets of the current water quality status and future  
142 scenarios based on the water quality model ensemble. Overall, harmonized water quality model  
143 output datasets based on multiple models are more robust than results of a single water quality  
144 model, providing several new opportunities that are briefly discussed below.

145

##### 146 1. *Identify robust water quality (pollution) hotspots*

147 Water quality MIPs can provide ~~more~~ better understanding of the robustness of ~~identification~~  
148 ~~identified of~~ water pollution hotspots under present-day and under future climate and socio-  
149 economic conditions than are currently available. Limited knowledge in particular exist on how  
150 pollution hotspots will develop over the next decades. Using results from multiple water quality  
151 models will provide a more comprehensive picture and assessment of the robustness of identified  
152 pollution hotspots under certain future scenarios than results of a single water quality model. This  
153 information is needed by decision makers and water managers to assess what adaptive solutions  
154 should be implemented in specific regions to improve the quality of water resources for human  
155 water uses and ecosystem health.

156

##### 157 2. *Assess robust trends in water quality*

158 Water quality model inter-comparison can be used to ~~identify~~ assess robustness of simulated trends  
159 in water quality. Various water quality models might show different responses and sensitivities to

160 changes in climate, land use, and socio-economic development. Ensemble simulations of water  
161 quality models might therefore be more useful than stand-alone models by providing a more  
162 comprehensive projection and increasing understanding of ~~and anticipating possible~~ future  
163 pollution changes.

164

### 165 *3. Improve understanding of processes and sources of water pollution*

166 Water quality MIPs can contribute to improved understanding of water quality processes and  
167 contribution of different pollution sources. Source apportionment across wide geographical  
168 domains can only be achieved through the use of large-scale water quality models, due to a lack of  
169 measurements at such scales [6,46]. Comparison of multi-water quality model outputs can provide  
170 a more comprehensive assessment ~~would allow more robust estimates~~ of sources and dominant  
171 pollution processes~~-. MIPs can identify agreement on identified pollution sources apportioned by~~  
172 different water quality models, which is ~~which are~~ needed to inform and develop effective water  
173 quality solutions in certain regions.

174

### 175 *4. Increase understanding of water quality model uncertainties*

176 Ideally, observed water quality monitoring records are used to validate water quality model  
177 estimates and assess model uncertainties for regions worldwide. However, ~~In~~ in comparison to  
178 river discharge and meteorological data, there is a significant lack of water quality measurements  
179 for many regions worldwide (e.g. Africa) [8] to evaluate water quality model performances and  
180 uncertainties [47]-. A consistent comparison of the results of different water quality models  
181 contributes to lending credibility to water quality estimates. In addition, sensitivity analyses,  
182 perturbing water quality models with different input will enhance understanding of water quality

183 model differences and uncertainties related to the structure and parameterization of different water  
184 quality models.

185

186

### 187 *5. Identify and set priorities for water quality data collection and monitoring*

188 Across many scientific domains, including water quality, monitoring and modelling are  
189 complementary approaches. The results of multi-model assessments of water quality could  
190 contribute to setting priorities and identifying regions for water quality data collection and  
191 monitoring [48].

192

193

### 194 **3.2 Challenges and recommendations for water quality MIP design**

195 A major challenge for water quality MIPs, so far, has been the limited number of large-scale water  
196 quality models per water quality variable (pollutant) available to compare and provide ensembles  
197 of water quality model results. However, several new large-scale water quality models have been  
198 developed over recent years (see Section 1; Supplementary Information Table S1) [47], providing  
199 new opportunities for water quality MIPs. Below we discuss the main challenges of designing a  
200 water quality model inter-comparison and propose recommendations to ensure useful harmonized  
201 water quality data are produced to suit the needs of decision makers and other users.

202

#### 203 *Challenge 1: Water quality models differ in spatial and temporal resolutions and domains*

204 Water quality models differ both in terms of spatial and temporal domains (e.g. use of different  
205 basin delineations and model simulation periods), as well as temporal and spatial resolutions. Some  
206 models simulate daily or monthly water quality estimates whereas others simulate annual average

207 values. Thus, when comparing models using different temporal resolutions, methods must be  
208 adopted to aggregate fine temporal scale estimates to compare with coarse-scale water quality  
209 estimates (e.g. select average year or use multiple years). In addition to temporal aspects, spatial  
210 resolution can also differ between models. Some water quality models are grid-based and spatially  
211 resolved at fine scales (e.g. WaterGAP-WorldQual). These are suitable to capture spatial  
212 heterogeneity of water quality, -while others are lumped at basins or sub-basins and are designed  
213 to compute basin-wide pollutant loadings or pollutant loadings of rivers to coastal zones (e.g.  
214 Global NEWS-2, ~~SPARROW~~). Overall, the scale for comparison is generally limited to lowest  
215 temporal and spatial resolution and domain. MIPs including lumped water quality models (or a  
216 combination of lumped and grid-based model water quality models) should therefore focus on  
217 basin aggregated level, comparing loadings/concentrations at basin outlets (river mouths). MIPs  
218 that solely include spatially-explicit (grid-based) water quality models are more suitable to compare  
219 spatial heterogeneity of water quality and relate to acceptable water quality levels for different uses  
220 (e.g. domestic, irrigation, industrial) and ecosystem health within a basin.

221

222 We present An-an illustrative example ~~is presented~~ for comparison of spatially-explicit organic  
223 pollution, focussing on simulated mean BOD concentrations derived from four large-scale grid-  
224 based water quality models, namely WaterGAP-WorldQual, GWAVA-WQ, VIC-QUAL and the  
225 global BOD model of Wen et al. [25] (Figure 2). We extracted Simulated-simulated mean BOD  
226 concentrations from the model of Wen et al. [25] and global simulation of VIC-QUAL [49] at  
227  $0.5^{\circ} \times 0.5^{\circ}$  ~~were extracted~~ for Europe. These We compared the mean BOD data ~~were compared~~ with  
228 high-resolution simulations ( $5^{\circ} \times 5^{\circ}$ ) of GWAVA-WQ [20,21] and WaterGAP-WorldQual [18] for  
229 Europe, which were aggregated to  $0.5^{\circ} \times 0.5^{\circ}$  using nearest neighbour resampling and averaged over  
230 the period 1990-2000 (Figure 2). Overall, These results show that organic pollution hotspots are

231 roughly comparable but some differences exist due to differences in model structure, input datasets  
232 (e.g. hydrology) and pollution sources considered. For instance, lower BOD concentrations  
233 simulated by the model of Wen et al. [25], can be explained by the fact that this model focusses  
234 solely on BOD loadings from urban population and livestock, while the other models also consider  
235 organic pollution from manufacturing.

236  
237 The importance of using similar temporal/spatial resolutions strongly depends on the purpose of  
238 the water quality model inter-comparison. For instance, full consistencies in temporal/spatial  
239 resolution amongst water quality models might be essential when aiming at understanding the  
240 water quality processes or quantifying model uncertainties, but possibly less so when the purpose  
241 of the inter-comparison is the identification (locations and intensity) of water quality hotspots  
242 (Table 1). Nevertheless, the use of similar spatial and temporal domains, and preferably also  
243 resolutions, of water quality models are overall recommended in water quality MIP design to  
244 provide consistent water quality model output.

245 **➔** *Recommendation 1: Use similar spatial and temporal domains and, preferably, also*  
246 *resolutions of water quality models in MIP design. However, not all models can be*  
247 *compared for the same purpose. For instance, MIPs of lumped water quality models should*  
248 *focus on pollutant loadings at river basin outlets, while MIPs solely including grid-based*  
249 *models can compare spatial water quality heterogeneity within basins.*

250

251

[Fig 2]

252

253

254 *Challenge 2: Water quality models differ in reported output variables*

255 Water quality models show a high diversity in output variables, which complicates a direct

256 comparison of model estimates. For instance, ~~Some~~ ~~some~~ water quality models focus on in-

257 stream concentrations (e.g. in mg/l) while other models simulate loads (e.g. in kg/yr) or area

258 specific yields (e.g. in kg/km<sup>2</sup> of basin/yr). In particular, nutrient models provide outputs for

259 different nutrient forms. Several models focus on total nitrogen (TN) and total phosphorous (TP)

260 (e.g. IMAGE-GNM, WaterGAP-WorldQual), whereas others (e.g. Global *NEWS-2*) simulate

261 different forms of nitrogen, phosphorus, carbon and silica. We present ~~An~~ ~~an~~ illustrative example

262 of comparison of river export of TN in loads (10<sup>6</sup> kg/yr) and yields (kg/km<sup>2</sup>/yr) for Global

263 *NEWS-2* [11] and IMAGE-GNM [14] models for a single year, 2000, ~~is presented~~-(Figure 3). The

264 Global *NEWS-2* model simulates different forms of nitrogen, i.e. dissolved inorganic nitrogen

265 (DIN), dissolved organic nitrogen (DON) and particulate nitrogen (PN). The individual loads for

266 each form were summed in order to provide TN estimates, which were then compared to

267 estimates of TN loads generated with IMAGE-GNM. We compared ~~The~~ ~~the~~ TN river export from

268 the grid-based IMAGE-GNM (0.5°) at basin outlet gridcells ~~was compared~~-with TN river export

269 from similar basin outlets of Global *NEWS-2*. Comparison of simulated TN loads (Figure 3a) and

270 yields (Figure 3b) from both global nutrient models shows rather similar basins with high or low

271 TN river export. Worldwide, lower values of TN river export were found for IMAGE-GNM (37

272 Tg N/yr) compared to Global *NEWS-2* (45 Tg N/yr). This might be related to differences in

273 model structure, process descriptions and input data. For instance, the approaches to simulate N

274 retentions in the terrestrial and aquatic systems differ greatly between both models, as do the use

275 of hydrological input data and basin delineations. The differences can also be explained by the

276 different purposes of the models: e.g. Global *NEWS-2* for scenario analyses and IMAGE-GNM

277 for improved, spatial-explicit understanding of the processes controlling nutrient export. Overall,

278 ~~it is~~we highly recommended ~~to group~~grouping of water quality models per pollutant form and  
279 focus on similar output variables (e.g. total nitrogen concentrations, loads or yields) and units  
280 (e.g. mg/l, kg/km<sup>2</sup>/yr), ~~in order to~~. This is needed to provide harmonized ensemble model outputs  
281 of water quality that can be used to identify in which regions models agree on simulated water  
282 quality changes, ~~that are useful for~~needed for water quality management and decision making,  
283 and to assess areas for model improvements. ~~In line with model intercomparison projects within~~  
284 the climate community (e.g. CMIP6), a minimum ensemble size of three models is desired to  
285 assess the robustness of identified trends [50].

286  
287 → *Recommendation 2: Use similar model output variables per pollutant form ~~for comparison of~~*  
288 *to provide insights in the robustness ~~large-scale water quality models of simulated pollution~~*  
289 *hotspots, trends and sources by large-scale water quality models.*

290 **[Fig 3]**

291  
292 *Challenge 3: Water quality models use different input datasets*

293 Various water quality models use different climate forcing datasets, hydrological (discharge,  
294 runoff) input, reservoir, land use and waste-water treatment data and assumptions. This complicates  
295 direct comparison and understanding of differences in simulated water quality results between  
296 models. Therefore the use of similar model input datasets in water quality MIP design is strongly  
297 recommended to provide consistent water quality model results that are meaningful for water  
298 pollution management, decision-making and other possible uses. In global hydrological and land  
299 surface modelling, the development of the WATCH Meteorological Forcing Data [51], was a major  
300 accomplishment facilitating inter-comparison projects such as WaterMIP and ISIMIP. In a similar  
301 way, producing different input datasets for water quality can be an important step to provide

302 harmonized water quality results. The level of harmonization on input data might differ, as certain  
303 water quality variables might have different driving forces and sensitivities to various input  
304 datasets. For example, river water temperature MIPs would prioritize the use of similar climate  
305 forcing data and hydrological datasets (reservoirs) into various water temperature models, while  
306 inter-comparison of organic pollution and nutrients models would ideally require harmonization  
307 also on land use and waste-water treatment input datasets. Furthermore, the main purpose for water  
308 quality model inter-comparison is important to consider. For instance, harmonization on all model  
309 input is preferred, but not absolutely trivial for the identification of present-day pollution hotspots.  
310 In contrast, strict harmonization on all model input ~~would be~~ essential when the focus of the MIP  
311 is on improved understanding of water quality processes and model uncertainties (Table 1).  
312 → *Recommendation 3: Harmonize relevant input datasets to provide consistent output for water*  
313 *quality model inter-comparison.*

#### 314 [Table 1]

315

#### 316 4. Discussion, conclusions and future outlook

317 Large-scale MIPs such as CMIP, AgMIP and ISIMIP have contributed to a better understanding  
318 of important components of the Earth system and climate change impacts on various sectors, as  
319 well as the associated model uncertainties- by bringing these modelling communities and together  
320 and consistently comparing model output. Given the recent proliferation of water quality models  
321 (Figure 1) and the fact that many people around the world are affected by water quality  
322 deterioration [8,9], pollution-driven water scarcity [52,53], and water security threats [54], there is  
323 now both an opportunity and a clear need to implement regional and global water quality MIPs.

324

325 Water quality MIPs can provide consistent, harmonized ensemble water quality model outputs,  
326 which is important for water policy and decision making [55]. Water quality MIPs can also  
327 contribute to improved understanding of pollution processes and pollution sources [6]. This is  
328 particularly important in world regions where observed water quality data are sparse (e.g. Africa,  
329 parts of southern America, Asia) [8]. In addition, water quality MIPs can be used to assess water  
330 quality trends and pollution hotspots, both for present-day and future scenarios. Such information  
331 is needed to assess potential strategies to provide clean water, both for human uses and ecosystems,  
332 and, to reduce pollution-driven water scarcity [52,53].

333  
334 To further improve large-scale water quality modelling we believe a more coordinated effort for  
335 inter-comparisons is recommended. This paper has discussed some of the main challenges and  
336 recommendations for water quality MIPs. Harmonising model output by using similar  
337 spatial/temporal resolution and domains (recommendation 1) and by using similar water quality  
338 output variables (concentration, loadings) (recommendation 2) is of major importance to provide  
339 consistent results. In addition, previous water quality MIPs have shown the importance of  
340 evaluating the performance of water quality models [41,45]. An important next step is to further  
341 harmonize on model input data (recommendation 3) and perform sensitivity analyses to improve  
342 understanding of uncertainties related to differences in water quality model structure. The extent  
343 of harmonization between input datasets will depend on the aim and ambition of the MIP. We think  
344 ~~t~~There is a clear need for MIPs comparing model output for a single quality variable. However,  
345 MIPs comparing model output for multiple water quality variables may also be useful to identify  
346 hotspots for water pollution for selected pollutants with similar sources [47,56].

347

348 Several MIPs of climate models and integrated assessment models have not only been informative  
349 for the scientific community, they have also influenced policy, especially in relation to climate  
350 change [57,58]. ~~We think a~~ standardized set-up and input dataset on water quality observation  
351 and model outputs for both current conditions and for future scenarios will be helpful to address  
352 future water quality and scarcity problems, and identify where water quality improvement are  
353 needed. This could facilitate the development of harmonized water quality assessments that can  
354 contribute to sustainable management and solution(s) identification supporting the achievement of  
355 clean water for all ([SDG6](#)) in coming decades.

356

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366

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Paper of special interest (\*) or outstanding interest (\*\*)

**Figures and Tables**

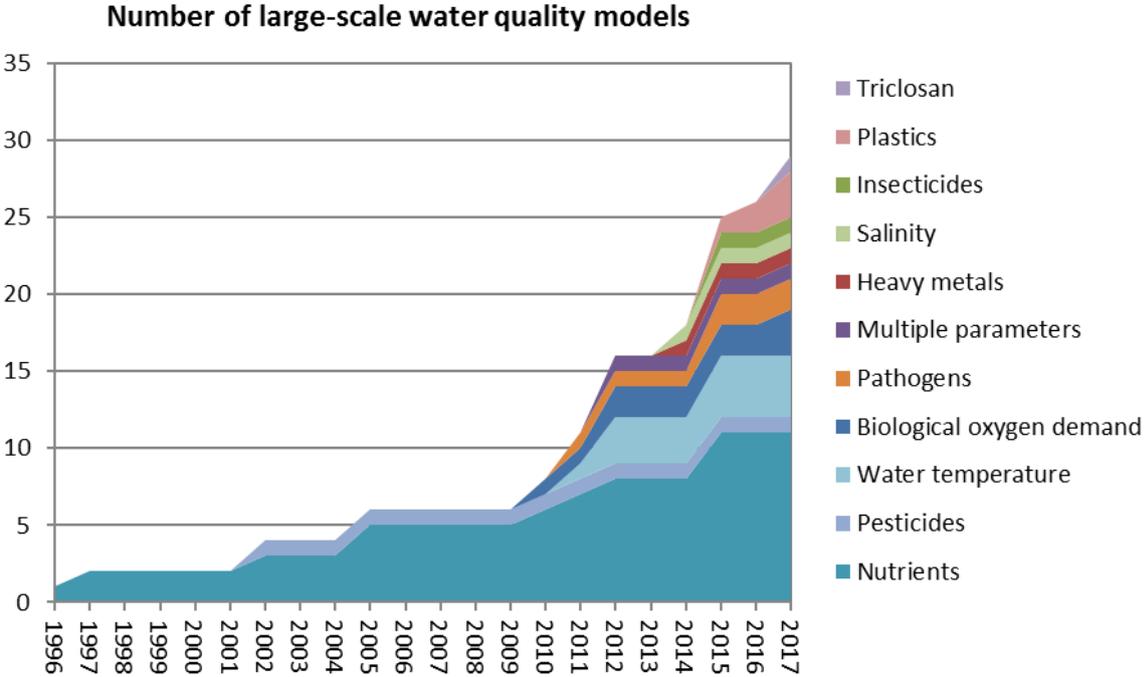


Figure 1: Increase in number of large-scale water quality models per water quality variable since the 1990s. A large-scale water quality model is defined here as a model capable of simulating one or more water quality variables on a scale that exceeds the size of one river basin. See Supplementary Information Table S1 for an overview of published studies per large-scale water quality model.

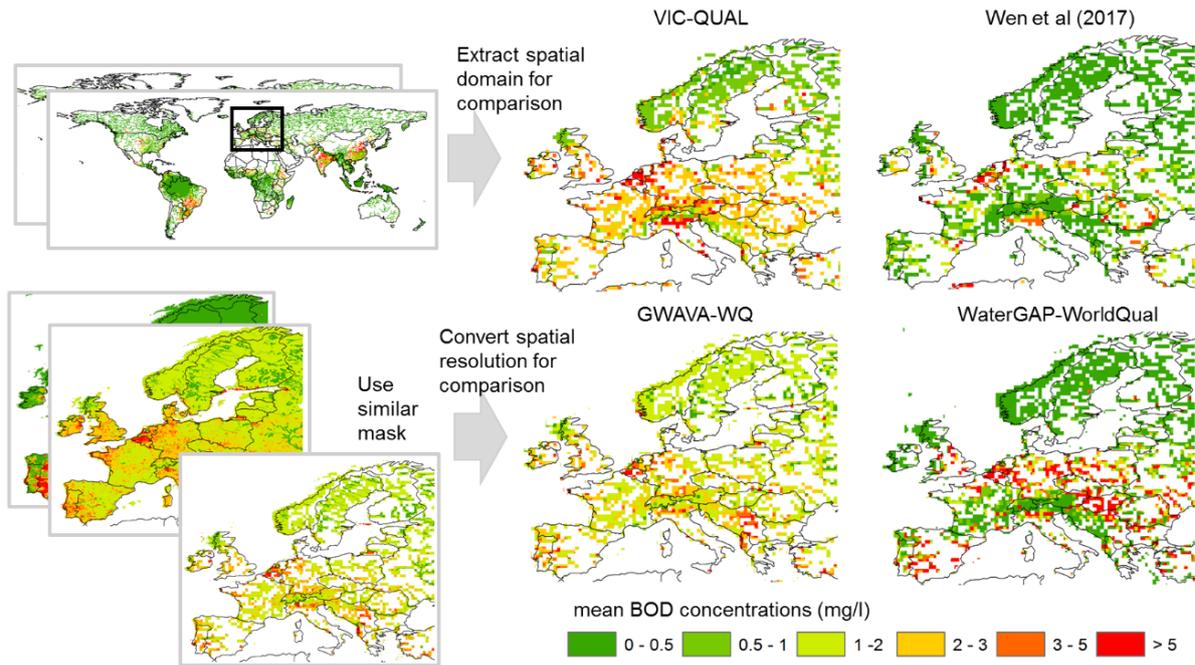


Figure 2: Model comparison of simulated mean BOD concentrations for Europe converting spatial domains and resolutions and aggregating to average values for the period of 1990-2000. Global gridded 0.5° simulations were extracted from the global models VIC-QUAL [49] and the global BOD model of Wen et al. [25] (upper panels), and BOD simulations from GWAVA-WQ [21] and WaterGAP-WorldQual [18] for Europe at 5'x5' were aggregated to 0.5°x0.5° (lower panels). The BOD model of Wen et al. [25] excludes grid cells with very low water availability, and a similar mask to exclude grid cells with low water availability was therefore applied to the other BOD models to allow for a consistent comparison.

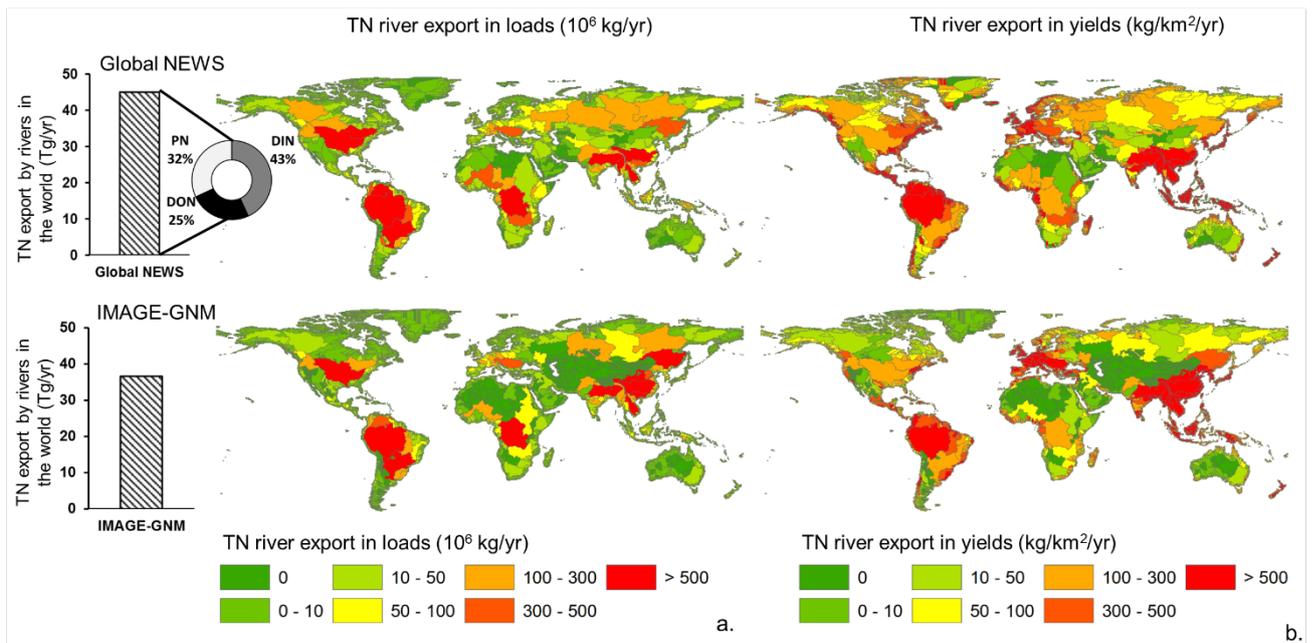


Figure 3. Use of similar model output variables and units for model inter-comparison of global total nitrogen (TN) river export in loads (a) and yields (b). Different nitrogen forms simulated by Global *NEWS-2* [11] (upper panels) were aggregated to compare with total nitrogen (TN) river export from IMAGE-GNM [14] (lower panels). Different nitrogen forms are dissolved inorganic nitrogen (DIN), dissolved organic nitrogen (DON) and particulate nitrogen (PN). TN river export from the grid-based IMAGE-GNM (0.5°) at basin outlet gridcells were compared with TN river export from similar basin outlets of Global *NEWS-2*.

Table 1: Relative importance of proposed recommendations for the five main aims of water quality model inter-comparison. Greyscale indicates the relative importance (light grey = relevant; middle grey = important; dark grey = highly needed (compulsory) to include in water quality MIP design)

<b>Aim</b>	<b>Recommendation</b>	R1: Use similar spatial/temporal domains and resolutions (harmonize on model output)	R2: Use similar model output variables for comparison (harmonize on model output)	R3: Harmonize on main model input datasets
1. Identify robust water quality (pollution) hotspots				
2. Assess robust trends in water quality				
3. Improve understanding of processes and sources of water pollution				
4. Increase understanding of water quality model uncertainties				
5. Identify and set priorities for water quality data collection and monitoring				