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1 **Perspectives and Challenges of Applying the Water-Food-Energy Nexus Approach to**
2 **Lake Eutrophication Modelling**

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16 **Abstract**

17 The water-food-energy (WFE) nexus is about balancing competing interests to secure the
18 sustainability of services provided by interconnected sectors. Ignoring the interconnections
19 could cause serious consequences. For example, eutrophication caused by overemphasizing
20 on food production maximization could threaten water security. Worldwide eutrophication
21 intensification is one of the most important causes of the lake water quality deteriorations.
22 Water quality models are usually important decision making tools for policy makers. This
23 study attempts to explore the possibilities of applying the WFE nexus concept into water

24 quality models. We propose the most significant challenge is lack of a common modelling
25 framework to streamline connections between up- and downstream models. As the most
26 important water quality issue, eutrophication modeling should increase its visibility in the
27 United Nations Sustainable Develop Goals.

28 **Keywords**

29 Lake eutrophication; water quality modeling and management; water-energy-food nexus;
30 sustainable development; challenges in integrations

31 **1. Introduction**

32 A disturbed water-food-energy (WFE) dynamics could intensify the nutrient discharges
33 from human activities to water, resulting in nutrient enrichment, subsequent eutrophication
34 and harmful algal blooms in the waterbodies [1–4]. About 150 Tg N is fixed from N₂ each
35 year by consuming large amounts of electricity (~3% of total electricity supply) [5], which
36 is far beyond the planetary boundary (~62 Tg/year) [6]. The majority of synthetic fertilizer
37 is applied in croplands [5, 7], but the low usage efficiency is resulting in a vast amounts of
38 excessive nutrient discharges into aquatic ecosystems [5]. On the other hand, urbanization
39 has aggravated imbalances between food productions and consumptions [8, 9]. Nutrients in
40 human excreta are regarded as contaminants and treated by wastewater treatment facilities
41 while simultaneously releasing GHGs such as CH₄ and N₂O [10, 11]. Water quality issues
42 (e.g., eutrophication, toxic algal blooms, coastal hypoxia and dead zones) [12] occurred in
43 waterbodies, but they are closely related with human activities in the catchment. Therefore,
44 it is acknowledged that water quality and resource management needs the efforts across
45 systems, across sectors and across disciplines [13–15].

46 Eutrophication is not a new topic, but it is one of the most troubling water quality issues
47 confronting human-being in recent decades [16]. Eutrophication can seriously damage the
48 functions of ecosystem services of waterbody on provisioning, regulating and maintenance
49 and cultural functions [17]. It was estimated that the combined costs were ~\$2.2 billion per
50 year as a result of eutrophication in the US freshwaters [18]. Natural eutrophication occurs
51 slowly in aquatic ecosystems, but this process could be accelerated by human activities by
52 several routes, such as intensified nutrient discharges and global warming [3, 19]. Since the
53 1990s, water quality has deteriorated in many rivers and lakes in Africa, Asia and Latin
54 America. Over 75% of closed waterbodies worldwide have experienced a certain degree of
55 eutrophication [20]. So far, most of human mitigation measures are devoted to reduction of
56 nutrient discharge into aquatic ecosystem (e.g., building WWTPs, reducing fertilizer usages,
57 afforestation). Regardless of economic costs, the mitigation measures seem to be successful
58 in some lakes, while fails in many other lakes [21]. Some other factors might also impact
59 the occurrences of algal blooms (e.g., climate changes). A recent study indicated that lake
60 warming might have counteracted the management effort to ameliorate lake eutrophication
61 since the 1980s [2].

62 Eutrophication modeling has provided an important tool to assess the ecological status of
63 lakes and pave the way to establish the sound management strategies in the eutrophication
64 mitigation and water quality improvement. These models were firstly developed in the
65 1970s (well-known as the Vollenweider models) and have been widely applied in the water
66 management. One primary goal of these models was to provide quantitative tools to predict
67 the responses of lakes and reservoirs to nutrient discharge and provide quantitative nutrient
68 reduction strategies [22]. For many cases, the nutrient loading was estimated by measured

69 nutrient concentrations and runoffs in the in-flow rivers [23–25]. Thus, nexus between lake
70 and watershed systems was weak and less quantified in most cases. Initially, water quality
71 model was simple and designed to characterize variations of in-lake nutrients with changes
72 of nutrient loadings [26]. With continuous developments of numeric calculation capacities,
73 more spatial (1D–3D) and temporal dynamics of hydrologic and ecological processes were
74 incorporated into the eutrophication modeling [25, 27–29]. These progresses have helped to
75 improve water quality management and set more appropriate control targets for the nutrient
76 loadings.

77 By addressing challenge from water, food and energy securities, nexus approach towards
78 resources management has been developed in the new frameworks of the UN Sustainable
79 Develop Goals (SDGs), and initiated in the implementations. Main objectives of the nexus
80 are to synthesize the individual systems of WFE and identify a coherent and harmonized
81 way for the sustainable development of cross-sectoral policies [30]. In this brief review, we
82 firstly sketched out the current conditions and the drivers for lake eutrophication. Then, we
83 summarized applications, advantages or limitations of eutrophication models which have
84 been widely applied. Finally, we analyzed the potential integrations between eutrophication
85 modeling and the WFE nexus and proposed potential challenges and opportunities ahead.

86 **2. Eutrophication and current conditions**

87 “Eutrophication” is originated from the Latin translation. “Eu” refers to “well”, and
88 “trophe” refers to the “nourishment”. Scientifically, “eutrophication” is used to denote a
89 process of nutrient enrichments from natural or anthropogenic sources and the subsequent
90 changes in trophic states of waterbodies. Usually, eutrophication could lead to the dramatic
91 growths of phytoplankton and depleting oxygen due to algal decay. From 1900s to 2000s,

92 the world population has increased from about 1700 to 7000 million. Synthetic fertilizer
93 has played an irreplaceable role to support the growing populations [5, 31]. For instance,
94 before 1900s, animal manure provided majority of phosphorus fertilizers. After 2000s,
95 ~80% of P fertilizer was contributed by phosphate rocks (~17 million tons of P), while only
96 3 million tons P are delivered to human diets [31]. Nitrogen (N), another essential element
97 for human, has similar patterns. Large volume of synthesized N fertilizer got lost during
98 food production [5]. Artificially fixed N originated from Haber-Bosch industrial production,
99 and agricultural fertilization is equivalent to N fixed from natural processes [32]. One third
100 of excessive N is transported from the lands to seas, leading to severe eutrophication issues
101 [33, 34].

102 Lake eutrophication has become common nowadays, as summarized in Table 1. In USA,
103 median TP in lakes was about 37 $\mu\text{g/L}$ in 2012. But, an unexpected increasing trend was
104 observed from 2007 to 2012 with causes unclarified [35]. In the European lakes, median
105 TP concentration was ~ 23 $\mu\text{g/L}$ in 2018 [36]. Now, many European lakes are recovering
106 from eutrophication following the controls of P inputs, providing a paradigm of successful
107 water managements [37]. Compared with developed countries, lake nutrient monitoring in
108 developing countries was usually performed in limited numbers of lakes and fragmented
109 time periods [38]. This might increase the uncertainties for scientific community to know
110 the overall nutrient conditions. In China, a nation-wide water nutrient monitoring network
111 has been set up since 2005, which provides us a window to explore the temporal nutrient
112 dynamics in the developing countries. Since the reform and opening in 1978, China has
113 experienced a period of rapid economic development. Since the early 2000s, many lakes
114 and reservoirs have become eutrophic. For instance, in the Lake Taihu, TP, TN and Chl a

115 concentrations in 2006 were over 100, 2000 and 50 $\mu\text{g/L}$, respectively [39–41]. In the Lake
116 Dianchi, TP, TN and Chl a concentrations in 2006 were about 200, 4000 and 40 $\mu\text{g/L}$,
117 respectively [40]. After the 2005, mitigation measures have been implemented to improve
118 water quality in China. The construction of wastewater treatment plants has grown rapidly.
119 In 2005, the percentage of municipal wastewater being treated on a national scale was only
120 $\sim 40\%$, while it had reached over 90% in 2017 [42, 43]. Nowadays, over 5,000 WWTPs in
121 operation could treat over $60 \times 10^9 \text{ m}^3$ domestic wastewater, which can largely reduce the
122 nutrient discharges into waters. An action aiming at reducing the fertilizer applications was
123 also initiated in 2015 [44]. Based on data set during 2006–2014, median TP concentrations
124 declined from 80 (3–247) $\mu\text{g/L}$ in 2006 to 51 (3–128) $\mu\text{g/L}$ in 2014 on the national scale [4].
125 Similar trends had also occurred for other contaminants such as COD and $\text{NH}_4^+\text{-N}$ [45].

126 **3. How to model eutrophication in lakes?**

127 In the past decades, aquatic modeling has been developed by environmental scientists as
128 important tools for water quality management. A recent review of the development in
129 eutrophication models for aquatic ecosystems pointed out the appealing diversity in this
130 field and advocated for maintaining the diversity; while called for the further efforts in
131 standardization, comparison and ensemble runs towards an interdisciplinary approach [46].
132 Some eutrophication models are simple and focused on changes of water qualities, while
133 other models could be far more complicated by coupling the hydro-ecological dynamics.
134 Eutrophication modeling for freshwater lakes and reservoirs started with the seminal work
135 from Vollenweider, Ran and Lee [47]. Based on the regressions between lake TP and Chl a
136 concentration, plankton biomass in lakes could be properly estimated [48]. Even nowadays,
137 these models (or derived equations) are also still very popular due to the simplicity in the

138 simulations [49]. After 1980s, 2D/3D ecological models for lake eutrophication started to
139 emerge in many countries. These models were capable of simulating the physicochemical
140 and biological processes in ecosystems through a series of equations [22, 50].

141 Since the 1990s, many process-based models such as the AQUATOX, CAEDYM, CE-
142 QUAL-ICM, EFDC and PCLake have been developed and applied in various waterbodies
143 (Table 2). Compared to statistical models concerning the causal relationships as a ‘black
144 box’, the process-based models need a theoretical and mechanistic understanding about in-
145 lake ecological processes. The ordinary or partial differential equations are fundamental for
146 simulations of the dynamic processes. Each model has its advantages and limitations, as
147 summarized by Eleni et al., 2017 [22]. For example, CAEDYM could simulate the grazing
148 pressures from zooplankton to phytoplankton, but it doesn’t consider sediment diagenesis;
149 EFDC may simulate high-resolution variation of internal nutrient process, but zooplankton
150 and detritus are excluded and there is a high demand for input data; PCLake could simulate
151 dynamics in the aquatic food chains, but needs a detailed information for trophic structures
152 for the model validations [38]. A recent advance in this field is the general framework for
153 aquatic biogeochemical models (FABM) [51] linking the multiple hydrodynamic (from 1D
154 to 3D) and biogeochemical models (e.g. FABM-PCLake) [52].

155 On the other hand, our understanding about the detailed ecological processes in aquatic
156 ecosystems is still advancing and the progresses will require further updates in the process-
157 based models. A typical example is about the pattern of nutrient limitations in the lakes.
158 Traditionally, ‘P-limitation’ for phytoplankton is usually assumed in the lakes; while recent
159 studies reported that N might be more important for many other cases [21]. The complex
160 interactions between N and P limitation in aquatic environments are still on debate. This

161 suggests that differential dynamic equations would be necessary for different lake types
162 [53]. Further, process-based models are usually more complicated than statistical methods.
163 Modeling results need calibrations and validations against ideally high temporal–resolution
164 monitoring data. These models had been developed and successfully applied in many lakes
165 [22, 38] and performed well in explaining limnology phenomenon [38, 54]. However, these
166 studies could only represent a small percentage of the lakes globally, resulting in potential
167 uncertainties between modeling performances and real conditions [38].

168 Nutrient loading and climate change are two key boundary conditions for the successful
169 simulations of the process-based models, since they are primary drivers for algae blooms in
170 the lakes [3, 4, 55, 56]. A better performance of process-based models also asks for a high-
171 quality input data, such as monthly or even daily–resolution data and specific types of
172 nutrients (such as $\text{PO}_4^{3-}\text{-P}$, $\text{NO}_3^-\text{-N}$, $\text{NH}_4^+\text{-N}$). For the lake ecosystems, high-quality nutrient
173 loading data to model lake water quality is thus far still scarce, particularly in the developing
174 countries [38]. With development of automatic observation technology, high temporal and
175 spatial resolution nutrient or weather monitoring data could be increasingly accessible. For
176 instance, China has set up a nation-wide nutrient monitoring network in major rivers and
177 lakes (<http://mee.gov.cn>). Information such as pH, DO, TN, TP and Chl a can be updated
178 every four hours. Similarly, the daily weather information such as rainfall, air temperature
179 and radiation, which is highly related to algae growth, is also available (<http://data.cma.cn/>).
180 This could provide lake the modelers an excellent opportunity to evaluate their results and
181 improve the reliability of the modeling results. However, this practice may be difficult for
182 the other developing countries to follow in the near future due to the costs and complexity
183 of setting up a monitoring network.

184 **4. How to integrate eutrophication modeling in the WFE nexus?**

185 Now, global community is facing unprecedented challenges that are directly linked to the
186 way we currently understand and manage our resources. WFE nexus framework and tool
187 offers a framework for systematic integrations of interconnected sectors in the planning and
188 decision making processes [57]. WFE approach is central to sustainable development, it is
189 thus important to update current eutrophication modeling under WFE framework. Water
190 quality issues occur in rivers or lakes, but they are caused by human activity in watersheds.
191 Mitigation measures aiming at improving the water quality are also closely connected to
192 social development and human activity. A good example to demonstrate the complicated
193 linkages is as follows: in order to reduce the nutrient inputs into the lakes, reductions of
194 fertilizer applications in the croplands are encouraged. However, reducing the fertilizer
195 usages could save electricity largely, since fertilizer production is a high energy-consuming
196 industry [5]. GHGs such as CO₂ might favor the algae growths in the lakes [55]. On the
197 other hand, reducing fertilizer application may also bring uncertainties in agricultural food
198 productions. It should be noted there is a clear division between the scientific communities
199 focusing on nexus approaches (e.g., data or social scientists) and those whose major focus
200 is on aquatic ecosystems (e.g., limnologists).

201 For the current 3D dynamic water quality models, there are three general categories of
202 variables: hydrologic variables (e.g., water flow, volume, lake stratification), environmental
203 variables (e.g., radiations, temperatures, nutrient loadings) and biological variables (e.g.,
204 planktons, benthos) [48]. A variety of internal reactions are simulated in the lakes, such as
205 denitrification, nitrification and mineralization. Reaction rate for internal processes was
206 determined by the water chemistry variables related with reactions and water temperatures

207 [24, 25, 58]. Janssen et al., 2019, has proposed that an ideal algal projection model should
208 include systems beyond the lakes, as follows: (I) environmental components (e.g., land
209 activity; human discharge; economic scenario); (II) network components (e.g., hydrological
210 process; damming or river connectivity; flow rate) and (III) aquatic ecosystem components
211 (e.g., internal process; aquatic system structures) [38]. Environmental component quantifies
212 various natural and anthropogenic nutrient sources into river networks. River network
213 describes transports of water and nutrient into lakes. Lake ecosystem component simulates
214 responses of water nutrients and algae growths to the climate changes and nutrient loadings
215 [38]. Actually, this ideal model has many potential interactions with the nexus framework
216 (Figure 1). For example, energy consumptions could produce GHGs and change climates,
217 affecting land nutrient transports in environment component, hydrology processes in
218 network component and aquatic structures in ecosystem component.

219 Environmental scientists have already attempted to link eutrophication with the drivers
220 in watersheds. Watershed models (such as SWAT, INCA, HSPF and SPAAROW) have
221 been developed to simulate impacts of human activities, economic scenarios and climate
222 changes on watershed nutrient retentions or outputs [59–63]. Derived information could be
223 applied as boundary conditions for eutrophication modeling. Several studies have been
224 performed to connect the watershed model with eutrophication model. For instance, Huang
225 et al., 2017, had coupled a Xinanjiang model with EFDC, and estimated the effectiveness
226 of watershed nutrient reductions in reducing algal blooms in the Lake Chao, China [25].
227 Debele et al., 2018, have integrated two powerful hydrological and water quality models
228 (SWAT and CE-QUAL-W2) to simulate combined processes of water quantity and quality
229 both in the upland watershed and downstream waterbody. Their results indicate two models

230 are compatible and could be applied to assess and manage water resources in complex
231 watersheds comprised of upland watershed and downstream waterbodies [15]. Zhang et al.,
232 2012, presents a MWRMS model to simulate hydrological and biogeochemical processes
233 in small prairie watersheds. Another route to connect eutrophication modeling with the
234 WFE nexus is climate changes. Climate change, largely linked with energy consumption,
235 could influence lake eutrophication by changing non-point nutrient inputs [64], changing
236 hydrologic processes [65] and impacting algae growths [66]. For example, by introducing
237 the MIROC5 model of CMIP5, Tong et al., 2020, has simulated impacts of lake warming
238 scenarios on intensifying internal nutrient cycling in lakes and increased dominances of
239 typical algae [67]. By interpreting high-resolution Landsat 5 satellite imagery, Ho et al.,
240 2019 investigated long-term trends in summer phytoplankton blooms for 71 large lakes and
241 indicated lake warming might already be counteracting management efforts to ameliorate
242 eutrophication [2]. All these examples provide the evidences that eutrophication modeling
243 could have different kinds of integrations with WFE approach, although such attempts on
244 integrations are only rudimentarily implemented and still rooted in eutrophication-centered
245 perspective.

246 It has been proposed that inclusion of the social-ecological dynamics is one of the major
247 improvements for the next generation aquatic ecosystem models in the Anthropocene.
248 Therefore, integrated WFE nexus and eutrophication models serve as unique tools to grasp
249 the interactions between human activities and environmental consequences. A prospective
250 strategy for such approach is to integrate the models addressing social-ecological dynamics
251 (e.g. IMAGE-GNM) [68] and models tackling lake eutrophication (e.g. PCLake) [54]. The
252 IMAGE-GNM models simulates social-ecological dynamics and synthesize the processes

253 in human society (e.g. agriculture, industrial, urbanization) that could potentially generate
254 excessive nutrient discharges and provides such external inputs as the major stressors to the
255 lakes. Eutrophication models in turn quantify the response of the water quality, evaluate the
256 status of the lake ecosystems towards critical transitions and inform the stakeholders the
257 reduction targets of nutrient loadings. The stakeholders could assess the tradeoffs between
258 social/economic development and ecological health/service and propose most effective lake
259 management and restoration policies (as indicated in Figure 1).

260 **5. Challenges in the integration and implications**

261 WEF nexus consists of various disciplines which uses different research methodologies
262 and inconsistent dimensions. Enhanced interaction between scientific communities working
263 on nexus approach and ecosystem management should be encouraged firstly. The stronger
264 integrations with the watershed activities, interactions between water quality and quantity
265 dynamics and interactions with the global climate changes are making the integrations of
266 eutrophication modeling into future nexus assessments increasingly feasible (Table 3).
267 However, we propose that following questions should be considered in advance for future
268 integrations:

269 **I. What does eutrophication modeling provide to the WFE nexus?**

270 WFE framework should take the eutrophication modeling as one important element. The
271 interdisciplinary nature of the WFE nexus requires that the framework should define the
272 interfaces where eutrophication are affected or might have effects [69]. The first step to
273 integrate the eutrophication modeling into WFE nexus is to prove that the modeling result
274 is useful in WFE framework. So far, most of eutrophication modeling targets at predicting
275 temporal dynamics of water nutrients, predicting occurrences of algal blooms and toxins

276 and provide control target for nutrient loading. These achievements could be important for
277 the water quality managers or limnologists, but are rarely admitted by the community from
278 other disciplines. It would be more valuable if the eutrophication modeling provides critical
279 information for the other systems either as inputs or feedbacks. A potential attempt could
280 be connected with the changes of ecosystem services due to the eutrophication. There is no
281 doubt that eutrophication damages the ‘ecological values’ of freshwaters. It was estimated
282 that the combined costs were about \$2.2 billion annually as a result of eutrophication in the
283 US freshwaters [18]. This could be a useful output under the WFE nexus perspective.
284 However, similar attempts have been quite limited so far.

285 **II. How to select a suitable model and smooth the input-output data?**

286 Due to differences in disciplines, multiple nexus modeling tools and methodologies have
287 been developed to solve target nexus problem. It can provide scientific communities the
288 opportunities to pick up the suitable model. However, it will also make researchers puzzled
289 when firstly stepping into the nexus approach [69]. We admit that every nexus problem
290 could be different, but a common framework would be helpful to use the nexus approach.
291 Based on general nexus framework, a list of candidate models should be evaluated for each
292 part of the nexus link; currently, there is no single model to simulate the entire WFE nexus
293 [69]. Study of the entire WFE nexus is achieved through linking the multiple models with
294 different functions. Thus, a common data transfer protocol should be developed to link the
295 different models. The candidate models all have different input and output format, different
296 spatial and temporal resolutions. It is important to make sure that the output from upstream
297 model could meet the input requirement of the downstream models.

298 **III. How to assess the uncertainties for sub- and entire systems?**

299 Uncertainties may propagate through the modeling chain, from the subsystem to whole
300 nexus [63]. The process-based eutrophication models could be assessed by the sensitivity
301 analysis or validated by input and output data. However, under the nexus framework,
302 different models derived from different disciplines could have different methods to validate
303 the results. A clear and unified uncertainty for the whole system is essential to obtain the
304 accurate and reliable results. For the eutrophication models, a validation with the historical
305 monitoring data is common. However, for economic models, uncertainties are evaluated by
306 other means. Thus, a unified method for the uncertainty analysis is highly necessary, so that
307 the outputs from different sub-models could be compared in the systematic framework.

308 **6. Conclusions**

309 Lake eutrophication is an important water quality issue worldwide, and it could seriously
310 damage the ecosystem services. Variety of eutrophication modeling has been developed but
311 it is rarely connected with the WFE nexus. Of course, it may be not necessary to consider
312 eutrophication modeling in all the nexus assessments. WFE nexus is central to sustainable
313 development, it is thus important to update the current eutrophication modeling under the
314 WFE nexus. The coupled watershed–lake modeling has provided us a good opportunity to
315 apply the eutrophication modeling in the nexus approach. However, challenges still exist,
316 and it needs efforts from respective scientific communities across disciplines and sectors.
317 We envision lake eutrophication models will continuously gain interests and its integrations
318 with WFE nexus could provide a valuable contribution to the watershed policymaking and
319 sustainability.

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325 **Conflict of interests**

326 The authors declare no conflict of interests.

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