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► **To cite this version:**

Brigitte Vinçon-Leite, Céline Casenave. Modelling eutrophication in lake ecosystems: A review. Science of the Total Environment, 2019, 651 (Part: 2), pp.2985-3001. 10.1016/j.scitotenv.2018.09.320 . hal-02070268

HAL Id: hal-02070268

<https://enpc.hal.science/hal-02070268>

Submitted on 10 Jun 2022

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1 *Modelling eutrophication in lake ecosystems: a review*

2 Brigitte Vinçon-Leite, Céline Casenave

3
4 **Abstract**

5 Eutrophication is one of the main causes of the degradation of lake ecosystems. Its intensification during the
6 last decades has led the stakeholders to seek for water management and restoration solutions, including those
7 based on modelling approaches. This paper presents a review of lake eutrophication modelling, on the basis
8 of a scientific appraisal performed by researchers for the French ministries of Environment and Agriculture.
9 After a brief introduction presenting the scientific context, a bibliography analysis is presented. Then the
10 main results obtained with process-based models are summarized. A synthesis of the scientist recommenda-
11 tions in order to improve the lake eutrophication modelling is finally given before the conclusion.

12
13 **1 Introduction**

14 Eutrophication of aquatic ecosystems refers to an ecological state, where biological processes driven by in-
15 creased nutrient loading from their watershed conducts to proliferation of primary producers (phytoplankton,
16 aquatic plants, cyanobacteria), hypoxia or even anoxia and loss of biodiversity. Worldwide, eutrophication is
17 one of the main causes of the degradation of the ecological state in inland and coastal waters. Eutrophication
18 has been observed since the beginning of the twentieth century in industrialized countries (*e.g.* Le Moal et
19 al., 2018; Moss, 2012; Takolander et al., 2017; Yao et al., 2018). However, during the last decade, eutrophi-
20 cation has become a more pregnant societal issue, encompassing many different stakes, from ecological to
21 economic and political, which must be tackled at the scale of the concerned territories by the involved stake-
22 holders.

23 Lakes and reservoirs are part of the hydrological cycle of their watershed. Fluxes are permanently exchanged
24 between the lake and the atmosphere, the ground and surface waters. Lakes play an essential role in the bio-
25 geochemical cycles of continental watersheds. Two processes drive these biogeochemical cycles, particularly
26 Carbon, Nitrogen and Phosphorus cycles: the primary production and the settling of particulate matter.

27 In lakes, the current velocities are generally low and the water residence time high. Therefore, lakes provide
28 us with a time-integrated response to the external forcing. The analysis of their time trajectory can allow us
29 to better understand the biological and physical, local and global pressures that they face (Perga et al., 2016;
30 Schindler, 2009).

31 Lake ecosystems are particularly sensitive to nutrient loading from their catchment because of the thermal
32 stratification of the water column during the period when the primary production is maximal (spring and
33 summer). The thermal stratification divides the water column into two layers: the upper layer, the warmer
34 and lighted epilimnion, where primary production occurs, and a colder deeper layer, the hypolimnion. Ther-
35 mal stratification occurs in all lakes but extending on different time scales. In shallow lakes, thermal stratifi-
36 cation hardly lasts more than a few hours or days. The main morphometric (depth, volume) and hydrological
37 (discharge of the tributaries, surface and land-use in the catchment) characteristics will determine the lake
38 vulnerability to eutrophication.

39 In the early 1960s, lakes were the first water bodies where eutrophication effects were observed, mainly on
40 the water resources used for drinking water supply (*e.g.* Dillon and Rigler, 1974a; Vollenweider and
41 Kerekes, 1982). Actually, lake eutrophication started in industrialized countries since the 1930s as it is indi-
42 cated by recent outcomes based on paleo-limnological studies. This is the case in Europe, for example for
43 Lake Bourget (France) where eutrophication appeared around 1933 (Giguet-Covex et al., 2010; Jenny et al.,
44 2013).

45 In the 1960-1980s, lake eutrophication was widely described, in particular in symposia devoted to this topic
46 like the Madison Symposium (National Academy of Sciences, 1969) or the Symposium of the American
47 Society of Limnology and Oceanography (ASLO) in 1971. Historically, the description of lake eutrophica-
48 tion was more directed to deep lakes, located in the Northern hemisphere (United States, Canada, and West-
49 ern Europe) and Australia. The general acceptance of lake trophic state classification, “oligotrophic”,
50 “mesotrophic” and “eutrophic” follows the studies of the Organisation for Economic Co-operation and De-
51 velopment (OECD) in the late 1970s (Vollenweider, 1975; Vollenweider and Kerekes, 1982).

52 The main effects of lake eutrophication are an increase of phytoplankton biomass, where cyanobacteria fre-
53 quently dominate, a decrease of water transparency and a clear difference between surface layers, rich in
54 oxygen, and the deoxygenated hypolimnion (Dodds, 2006; Wetzel, 2001). Hypoxia in the hypolimnion leads

55 to an internal phosphorus load released by the sediment, which in turn amplifies the eutrophication of the
56 system (Dodds, 2006).

57 Eutrophication has been one of the main threats for water quality in lakes and reservoirs since the 1960s. In
58 spite of number of research works conducted during the last five decades, eutrophication remains a major
59 concern worldwide (Smith et al., 2006). More than 40% of lakes are eutrophic and affected by algal blooms
60 (Bartram et al., 1999). The issues to be addressed still regard interactions between nutrients, principally
61 phosphorus which is generally the main cause of lake eutrophication, and the ecological functioning. New
62 manifestations of eutrophication have emerged during the last two decades (Anderson et al., 2012; Le Moal
63 et al., 2018; Pomati et al., 2017). Among the phytoplankton species, cyanobacteria have gained an increased
64 interest, due to the worldwide occurrence of their blooms. The increasing frequency of cyanobacteria blooms
65 might be linked to climate change.

66 The management and restoration solutions to control eutrophication must be supported by scientific out-
67 comes, including modelling approaches. Since the 1970s and the awareness of the negative impact of eutro-
68 phication on lake ecosystems, numerical modelling was considered as an interesting tool (Imboden, 1974;
69 Vollenweider, 1975; Vollenweider and Kerekes, 1982). Many models were developed, often to obtain pre-
70 dictive tools used as support for lake management and to define targets of nutrient loading reduction by the
71 catchment. The model key state variables are those that link primary production to nutrients, principally
72 phosphorus, nitrogen and sometimes silica (De Senerpont Domis et al., 2014; Reynolds et al., 2001).
73 Cyanobacteria growth also raises new modelling issues to represent processes such as nitrogen fixation, up-
74 take of nutrient organic forms and mobility of the cells.

75 In order to support public decision-making, issues raised by public entities, for example a ministry, can be
76 addressed in the form of a multidisciplinary critical assessment of available scientific knowledge, called col-
77 lective scientific expertise. In 2016, two French ministries respectively in charge of ecology and agriculture,
78 initiated a collective scientific expertise (Expertise Scientifique Collective, ESCo in French), bringing to-
79 gether scientific knowledge available on the eutrophication issue (Pinay et al., 2017). The objective was to
80 improve the consistency and effectiveness of public action on eutrophication control. One chapter of the
81 scientific expertise report was devoted to eutrophication modelling (Crave et al., 2017). This chapter in-
82 cluded five sections respectively entitled “Modelling of non-point nutrient loading in the catchment”, “Mod-

83 elling in-stream processes”, “A focus on sediment transport modelling”, “Modelling eutrophication in coastal
84 ecosystems” and “Modelling eutrophication in lake ecosystems”. A review of marine eutrophication models
85 derived from this scientific expertise study can be found in (Ménésguen and Lacroix, 2018). The paper pre-
86 sented hereafter is based on the chapter focusing on lake eutrophication modelling and including a large re-
87 view of modelling studies.

88 The bibliographic corpus that we considered is composed of 438 references obtained by using the biblio-
89 graphic search tool proposed by Web of Science (see Appendix 6.1 for details). The paper is organized as
90 follows. In section 2, the bibliographic corpus is analysed according to the following items: study sites, ob-
91 jectives, model typology and main research topics. Additional statistics about the number of publications and
92 citations; the general categories, research areas and journal titles; and the keywords of the references includ-
93 ed in the bibliographic corpus are given in Appendix 6. Section 3 is dedicated to the modelling results ob-
94 tained with process-based models. Finally we summarize the scientist recommendations in order to improve
95 the lake eutrophication modelling in section 4, and we raise some key issues for future achievements in this
96 research field in the conclusion section.

97

98 **2 Bibliography analysis**

99 **2.1 Study sites**

100 Several lakes have been considered as case studies for the application of eutrophication models. An auto-
101 matic search routine was implemented to search for the names of lakes in the title, abstract and keywords of
102 the references of the bibliographic corpus. It led to a list of 118 lake names and 230 references. The reparti-
103 tion of the references according to the continent, the country and the name of the lakes is given in Table 1.
104 The evolution over the time of the number of publications according to the continent of the studied lake is
105 given in Figure 1.

106 **Table 1. Number of publications depending on the continent, the country and the name of the studied lake. Only the countries**
107 **and the lakes that have been found in three or more than three publications are listed.**

108

109 **Figure 1. Time evolution of the number of publications according to the continent of the studied lake.**

110

111 The most studied lakes are located in North America (mostly in the USA and Canada) and Asia (in China,
112 Japan, Turkey and Russia). Lakes of Western Europe (in The Netherlands, Estonia, Switzerland and Ger-
113 many) and Northern Europe (in Finland and the United Kingdom) also receive special attention. The Great
114 lakes or Laurentian lakes (Lakes Erie, Ontario, Michigan, Superior and Huron) located between the USA and
115 Canada are the subject of numerous publications. Apart from them, we can mention the particular case of
116 Lake Taihu (China) that is intensively studied (26 papers), as much as for Lake Erie but at a different pace.
117 Publications on Lake Erie started in 1984 and on Lake Taihu in 2004. Among the other lakes, there are many
118 large lakes with a surface area over 100 km², as it is the case of Lake Dianchi (China), Kinneret (Israel),
119 Balaton (Hungary), Chaohu (China), Okeechobee (USA), Peipsi (Finland) and Kasumigaura (Japan).
120 Regarding the time evolution, the lakes that were studied during the 1970s and the 1980s are mainly located
121 in North America (Ditoro et al., 1987; Snodgrass, 1987, 1985). In the 1990s, modelling works were then
122 carried out on lakes from Western Europe (Asaeda and Van Bon, 1997; Hollander et al., 1993). And since
123 2000, there has been a significant increase in modelling studies conducted on Chinese lakes, particularly
124 since 2010 (Hou et al., 2004; Huang et al., 2012; W. Li et al., 2014). In parallel, lake ecosystems from South
125 America (Fragoso et al., 2008), Southern Europe (Alonso Fernandez et al., 2014), Middle East such as
126 Karaoun reservoir in Lebanon (Fadel et al., 2017) but mainly Lake Kinneret in Israel (Bruce et al., 2006; Gal
127 et al., 2009) and Africa (Asaeda et al., 2001) were also modelled.
128 Finally, models have also been applied to high-altitude or high-latitude lakes in recent years (Patynen et al.,
129 2014; Romshoo and Muslim, 2011). Similarly, the preservation of ecological continuity in the urban and
130 peri-urban environment and the promotion of Nature-based solutions for the urban water management led to
131 recent modelling works of small urban lakes (*e.g.* Gong et al., 2016; Soullignac et al., 2017).

132

133 **2.2 Modelling objectives**

134 Several purposes have led to the development of lake eutrophication models. Although eutrophication mod-
135 els are not only used for management purposes but also for research (Simonsen and Dahl-Madsen, 1978;
136 Vanhuet, 1992), we will focus in this paper mainly on the management objectives. In the keyword analysis,
137 the words “management”, “simulation”, “prediction” and “restoration” appear respectively, in 54, 49, 31 and

138 22 references of the bibliographic corpus, which represents 12%, 11%, 7% and 5% of the references. This
139 shows how lake eutrophication is a concerning problem for which practical solutions are needed.

140 In the 1970s, the OECD model (Vollenweider, 1975), that has been calibrated on a data set coming from
141 more than 200 lakes of several continents, was used to predict the eutrophication response to phosphorus
142 loading. The nutrient load limits in the USA and Canada have been established from this model.

143 Some models have been used to assess the conditions for achieving regulatory or management objectives.
144 For example, the 1D vertical model DYRESM-CAEDYM was used to compute the level of phosphorus in-
145 put reduction necessary to make the ecological status of Lake Ravn (Denmark) comply with the requirements
146 of the European Water Framework Directive (Trolle et al., 2008).

147 Models are also developed to perform numerical experiments. Recently, the sharp increase in the number of
148 reservoirs worldwide (World Commission on Dams, 2000), for irrigation, drinking water production and
149 hydroelectricity, has led researchers to investigate the effects of eutrophication on the carbon and greenhouse
150 gas cycle in these water bodies (Chanudet et al., 2012; Stepanenko et al., 2016). Models are also used to
151 predict the functioning and the impact of a reservoir that is expected to be built (Inkala et al., 1998). Con-
152 versely, some papers focus on the simulation of the impact of climate changes on lake eutrophication (Elliott
153 and Defew, 2012; Hassan et al., 1998; Schwefel et al., 2016). It includes the increase of temperature (Mark-
154 ensten et al., 2010) and the intensification of extreme climatic events such as floods (Brito et al., 2017) or
155 storms (Schwalb et al., 2015).

156 Model of lake eutrophication are also often used to predict the evolution of variables of interest. In the short
157 term (one or two weeks), the objective can be to predict algal blooms, particularly cyanobacteria blooms. It
158 makes it possible to anticipate the measures to be taken depending on the water body use: recreational activi-
159 ties such as bathing, production of drinking water, etc. (Huang et al., 2015, 2012; W. Li et al., 2014; Reckna-
160 gel et al., 2016). Over longer time-scales, models are used to predict the response of lake ecosystems to cli-
161 mate change scenarios or local changes in nutrient input (Chapra and Canale, 1991; Pipp and Rott, 1995),
162 sometimes with a special focus on cyanobacteria dynamics (Howard and Easthope, 2002; Markensten et al.,
163 2010; Varis, 1993).

164 Finally, models are also developed to test some control strategies for the restoration of lakes (*e.g.* Sagehashi
165 et al., 2001). The reduction of nutrient loads is the most studied strategy (*e.g.* Lindim et al., 2015; Ozkun-
166 dakci et al., 2011). Some papers focus on biomanipulation which consists in adding or removing species
167 from the ecosystem (Jayaweera and Asaeda, 1996; Ogilvie and Mitchell, 1995; Sagehashi et al., 2001). Other
168 alternative lake restoration techniques are studied, such as sediment dredging (Sagehashi et al., 2001), water
169 diversion (Liu et al., 2014), addition of macrophytes (Xu et al., 2014, 1999) or hypolimnetic oxygenation
170 (Moore et al., 1996; Sahoo and Luketina, 2003; Singleton et al., 2010; Toffolon and Serafini, 2013).

171

172 **2.3 Model typology**

173 The scientific community early recognized the value of mathematical modelling for the study of lake ecosys-
174 tems. Researchers have developed numerous models of various types. Recent reviews of lake modelling de-
175 velopments can be found in (Bhagowati and Ahamad, 2018a; Jørgensen, 2010b). Depending on how the
176 ecosystem is represented mathematically, we can distinguish several classes of models (see for example
177 (Jørgensen and Fath, 2001; Mooij et al., 2010a)). Thus, models are generally first separated in two classes:
178 empirical models and mechanistic models (Fornarelli et al., 2013).

179 **2.3.1 Empirical models**

180 Empirical models, also called data-oriented models (Afshar et al., 2012) or data-driven models (Elshorbagy
181 and Ormsbee, 2006) are derived from the available data sets. They mainly consist in statistical relationships
182 (called transfer functions) between predictor variables and response variables of interest. The first empirical
183 models that were developed were regression models that assume linear relationships between the variables as
184 it is the case for the nutrient-chlorophyll relationships given in (Dillon and Rigler, 1974a; Reckhow, 1993).
185 Empirical models present several advantages: they require little *a priori* knowledge about the ecosystem
186 processes and the data themselves; few data and “simple mathematics are needed” and these models are ge-
187 neric and “give good predictions for a group of lakes” (Vanhuët, 1992). However, when applied to an indi-
188 vidual lake, empirical models often lead to large uncertainties. According to Vanhuët (1992), “empirical
189 models are often applied if only mean annually values are of interest”. However, due to the rapid progress in
190 available computational power, and to the increasing use of high frequency measurement systems based on

191 *in situ* sensors, interest in empirical models is still growing. These models are used for different purposes, for
192 example to re-analyze statistical relationships between nutrients and chlorophyll in different contexts (Brown
193 et al., 2000; Huszar et al., 2006). New statistical approaches are also proposed to improve the quality of the
194 models. For example, quantile regression is applied instead of ordinary least square regression in (Xu et al.,
195 2015) and a Bayesian approach is used to link nutrient and chlorophyll concentrations in (Freeman et al.,
196 2009). Bayesian model averaging has also been proposed to predict the occurrence of harmful algal blooms
197 (Hamilton et al., 2009). However, these models provide results associated with a very large level of uncer-
198 tainty and over time scales too long to study the short-term response to a decrease in nutrient inputs by the
199 watershed; they therefore lack precision for use by managers (Reynolds and Elliott, 2010).

200 Statistical models of the 1970s and 1980s have evolved significantly over the last decade towards "data-
201 driven" models. Such models need large datasets that were not available in the past, but that lake monitoring
202 systems are now able to collect. Artificial neural networks (ANNs) are now commonly used to study lake
203 eutrophication (Chen and Liu, 2014; Jeong et al., 2015; Millie et al., 2006; Rankovic et al., 2010), because of
204 "their recognized capability in predicting highly nonlinear and complex relationships" (Fornarelli et al.,
205 2013). However, if ANNs provide interesting prediction tools, their construction is a "highly demanding
206 task, particularly when dealing with short and noisy ecological data" (Chaves and Kojiri, 2007; Fornarelli et
207 al., 2013; Kim et al., 2012). Other data-driven models using machine learning techniques such as tree-based
208 models (Fornarelli et al., 2013; Jung et al., 2010; Peretyatko et al., 2012), support vector machines (Diaz
209 Muniz et al., 2015; Garcia-Nieto et al., 2018; Yunfeng Xu et al., 2015) or random forests (Hallstan et al.,
210 2012) are also proposed. For short-term (day to weeks) forecast, such data-driven models give good results,
211 but for the simulation of long-term prospective scenarios, they hardly can be used as it is necessary to in-
212 clude knowledge about the driving processes.

213 **2.3.2 Mechanistic models**

214 Mechanistic models, also called process-oriented models (Arhonditsis and Brett, 2004), process-based mod-
215 els (Fornarelli et al., 2013) or theoretical models (Vanhuet, 1992), are based on the *a priori* knowledge of the
216 driving processes of the ecosystem. Most of them consist in a set of differential or difference equations
217 which describe in details the biogeochemical processes and whose solution is obtained by numerical meth-

218 ods. Several review papers focusing on mechanistic models have been published (*e.g.* Anagnostou et al.,
219 2017; Arhonditsis and Brett, 2004).

220 In the 1980s, mechanistic models often compute the steady-state concentration of variables, leading to
221 nonlinear static relationships between variables of interest (*e.g.* Imboden, 1974; Schnoor and O'Connor,
222 1980; Vollenweider, 1975). These models are called “input-output” models (Vollenweider, 1975) or black-
223 box models (Teruggi and Vendegna, 1986) and are sometimes considered as empirical models whereas their
224 structure is directly deduced from dynamic equations of biogeochemical processes. The data that generally
225 come from a group of lakes, are only used to identify the model parameters with statistical methods. This
226 approach has been widely used to estimate the trophic state of numerous lakes (*e.g.* Jones and Bachmann,
227 1976; Dillon and Rigler, 1974b). As they are based on a steady-state assumption, input-output models fail to
228 “predict the dynamic trend of eutrophication in a large reservoir with temporal variation in inflow and stor-
229 age” (Afshar et al., 2012). Moreover, these models “do not describe the biological variables which are of
230 main interest” and “do not take into account the influence of biological processes on the model parameters”
231 and some “important interactions between several phytoplankton limiting factors, light, phosphorus, nitro-
232 gen” (Simonsen and Dahl-Madsen, 1978).

233 Most mechanistic models are dynamic. Mooij et al. (2010) make the distinction between “minimal dynamic
234 models”, “complex dynamic models” and “structurally dynamic model”. Minimal dynamic models are sim-
235 ple and composed of only a few differential or differences equations; they “often generate a hypothesis about
236 a possible cause of a phenomenon that would not easily be arrived at intuitively” (Mooij et al., 2010a). On
237 the contrary, complex dynamic models (*e.g.* CAEDYM, PCLake, DELWAQ) include numerous variables
238 and processes and are designed to be used as a virtual reality for the simulation of the whole ecosystem.
239 They are therefore often coupled with a detailed hydrodynamic model and validated on field data. A com-
240 parison between nine complex dynamic models commonly used to study eutrophication can be found in
241 (Anagnostou et al., 2017). Structurally dynamic models have then been proposed to add flexibility in the
242 structure of the models (Jørgensen, 2015). The idea is to make the model parameters vary over time, based
243 on the expert knowledge or by optimization of a well-chosen goal function. Kalman filter (Huang et al.,
244 2013) is based on similar idea: by addition of a “correction” term in the equations of the model, it enables to
245 adjust the model variables to the measurements. Finally, we can mention the particular case of the BLOOM

246 model (Los, 1980) which also relies on optimization techniques: it is based on the computation of the opti-
247 mal species composition via linear programming.

248 In the above-mentioned models, the ecosystem is described at the population level. The need to take into
249 account some specific features of the populations, such as size distribution or other traits, led the researchers
250 to use the individual-based approach (DeAngelis and Mooij, 2005). As it is « too computationally demanding
251 to model all individuals separately » (Mooij et al., 2010a), derived approaches that are computationally more
252 efficient, have been proposed, such as super-individual models, physiologically structured population mod-
253 els, stage-structures biomass models, and trait-based models. Mention should be made of other approaches
254 such as energy system language (*e.g.* Rivera et al., 2007).

255 Mechanistic models have been applied to many lakes (*e.g.* Cui et al., 2016; Hou et al., 2004; Takkouk and
256 Casamitjana, 2016), and their contribution to the study of the spatio-temporal dynamics of ecosystems is
257 widely recognized. In particular, hydrodynamic processes are represented accurately. However with regard
258 to biological processes, because of the complexity of the process interplay, and the lack of knowledge,
259 mechanistic models still need to be improved. Mechanistic models are already complex and involve a large
260 set of parameters (sometimes more than 100) to be calibrated. As a consequence, the outcomes of simulated
261 scenarios are hampered with great uncertainty (Gal et al., 2014). The calibration itself is a difficult task be-
262 cause it necessitates the use of extensive data sets (Elshorbagy and Ormsbee, 2006) and because the simula-
263 tions, particularly when coupled with 3D hydrodynamic models, are computationally demanding. Limita-
264 tions concerning their application at the decision-making level have been emphasized (Fornarelli et al.,
265 2013). Nevertheless, deterministic models remain best suited to simulate the spatio-temporal response of lake
266 ecosystems to forcing change scenarios. Moreover the increase of the computational power should facilitate
267 the use of such models in the future.

268 Note that mechanistic models are often deterministic but the stochastic nature of the events and pathways
269 leading to eutrophication should encourage the use of stochastic components (Kutas and Toth, 1985; Sarkar
270 and Chattopadhyay, 2003; Wang and Qi, 2018).

271

272 **2.3.3 From box models to 3D models**

273 To reproduce accurately the ecosystem dynamics, mechanistic models are frequently coupled with a hydro-
274 dynamic model that can be quite simple, simulating only the water temperature and the regime of tempera-
275 ture stratification and mixing or more complex, simulating also the current velocities and patterns.

276 The spatial dimension of the coupled models varies from zero (box models): in that case “the water body of a
277 lake or of each box within a lake is represented as a completely mixed stirred tank reactor” (Nyholm, 1978),
278 to three : the spatial heterogeneity of the ecosystem is taken into account in all three dimensions. If a box
279 model alone cannot account for the lake spatial heterogeneity, this can be obtained using a set of intercon-
280 nected box models (Muraoka and Fukushima, 1986; Nyholm, 1978). For example, Smiths lake has been
281 divided into 11 boxes, each of them is represented as a well-mixed reactor, connected to its neighbouring
282 boxes through fluxes (Everett et al., 2007). For the vertical dimension, some models simulate the thermal
283 stratification by using 2-box models with one box for the epilimnion and one box for the hypolimnion (Frisk,
284 1982; Imboden, 1974; Imboden and Gächter, 1978; Rodriguez Reartes et al., 2016).

285 Vertical 1D models are also frequently used to simulate the thermal stratification and its influence on phyto-
286 plankton, nutrient and oxygen dynamics (Bell et al., 2006; Fennel et al., 2007; Trolle et al., 2008). 2D mod-
287 els, more rarely used, are developed for large but shallow systems where thermal stratification is negligible
288 (Fragoso et al., 2008; Huang et al., 2012; Zhang et al., 2008). 3D models appeared in the early 2000s (Kuo
289 and Thomann, 1983), but it was in the 2010s, due to the increase of computational power and of *in situ*
290 measurements, that 3D models have been increasingly applied on lakes (Carraro et al., 2012; Deus et al.,
291 2013; Leon et al., 2011; Schwalb et al., 2015; Soullignac et al., 2017).

292 The coupling of models can be a difficult task. The Framework for Aquatic Biogeochemical Models
293 (FABM) has been developed to facilitate the coupling between several hydrodynamic models and ecological
294 models (Trolle et al., 2011a).

295 **2.4 Main research topics studied with lake models**

296 As shown by the keywords analysis (see appendix 6.4), the models can represent different components of
297 the ecosystem. In the following section, we will analyse more in details how these components are repre-
298 sented: (1) phytoplankton; (2) nutrients; (3) sediments; (4) oxygen; (5) cyanobacteria.

299 **2.4.1 Phytoplankton**

300 A significant number of references of the bibliographic corpus (115 references, 26% of the total) are marked
301 with the keyword “phytoplankton” which shows the importance given to the modelling of phytoplankton
302 dynamics (Elliott and Thackeray, 2004; Frisk et al., 1999; Hillmer et al., 2008; Reynolds and Irish, 1997;
303 Rukhovets et al., 2003; Seip, 1991).

304 In many models, in particular empirical models but also water quality models, only the total phytoplankton
305 biomass is represented. In recent years, the study of changes in phytoplankton community composition has
306 received special attention, leading to the development of phytoplankton succession models (Rigosi et al.,
307 2010). The phytoplankton community is divided into different groups, either by modelling all the species
308 individually or by incorporating community information into the models (Hallstan et al., 2012). The phyto-
309 plankton modelling relies on a representation of the functional characteristics of species (Hallstan et al.,
310 2012; Jones and Elliott, 2007; Kerimoglu et al., 2017a; Mieleitner and Reichert, 2008, 2006). In a few cases,
311 models seek to represent the functioning of individuals in a phytoplankton population during the different
312 stages of their life cycle through the use of "agent-based" or "individual based models" (Hellweger et al.,
313 2008). These models can be used to predict either short-term changes in phytoplankton community composi-
314 tion (Huang et al., 2014, 2012), or medium to long term changes (Elliott et al., 2005; Markensten et al.,
315 2010). 3D models allow for better consideration of spatial heterogeneities in phytoplankton development
316 (Hillmer et al., 2008; Leon et al., 2012, 2011).

317 Some studies focus on the modelling of particular processes, such as: (1) the influence of physical function-
318 ing on phytoplankton dynamics (Bernhardt et al., 2008; Elliott et al., 2009; Elliott and Defew, 2012; Gulliver
319 and Stephan, 1982; Jones and Elliott, 2007; Na and Park, 2006; Patynen et al., 2014; Verhagen, 1994); (2)
320 the relationships between external or internal nutrient inputs and phytoplankton dynamics (Burger et al.,
321 2008; Cui et al., 2016; Li et al., 2015); (3) the interactions between phytoplankton and macrophytes (Asaeda
322 et al., 2001).

323 **2.4.2 Nutrients**

324 Within the bibliographic corpus, numerous references, precisely 117 references (17%), 46 references (11%)
325 and 74 references (17%), are marked respectively with the keywords “phosphorus”, “nitrogen” and “nutri-
326 ent” (see section **Error! Reference source not found.**). These references do not necessary focus on the
327 modelling of nutrients only. Phosphorus is the most studied nutrient as it is generally considered as the main

328 limiting nutrient of phytoplankton growth in most lakes (*e.g.* Schindler, 2006; Sondergaard and Jeppesen,
329 2007).

330 As for phytoplankton, some models – mostly the empirical and static ones – only represent the total phos-
331 phorus (Dillon and Rigler, 1974b, 1974a; Nürnberg and LaZerte, 2004; Seo and Canale, 1996) and/or the
332 total nitrogen concentrations (Brown et al., 2000; Ji et al., 2014; Milstead et al., 2013; Reckhow, 1993).

333 However, to describe correctly the nutrient cycle and its dynamics, the different nutrient forms are often dis-
334 tinguished. The phosphorus is generally divided into two groups: particulate and dissolved phosphorus (Lung
335 et al., 1976). Other models make the distinction between organic and inorganic nutrients (Deus et al., 2013).
336 Among the dissolved inorganic nitrogen pool, nitrate and nitrite are often separated from the ammonium
337 (Lindim et al., 2015; Wu et al., 2017), the nitrification and denitrification processes being considered as es-
338 sential for the ecosystem dynamics. In complex models such as CAEDYM (Hipsey et al., 2011), in addition
339 to the forms previously mentioned (particulate/dissolved, organic/inorganic, nitrate/nitrite/ammonium), the
340 organic compartments can also be divided into labile and refractory forms.

341 Finally the carbon, nitrogen and phosphorus contents of biological organisms such as zooplankton, phyto-
342 plankton, bacteria or macrophytes can be described, through the use of either constant or variable
343 stoichiometric ratios (see CAEDYM model (Hipsey et al., 2011)). Fernandez et al. (1997) introduced as
344 model variables the soluble reactive, the soluble non-reactive and the particulate phosphorus cell quotas in
345 phytoplankton, which are defined as phosphorus amount per biomass unit (Droop, 1968). The phosphorus
346 content in shoots, secondary shoots and roots of macrophytes can also be included (Asaeda et al., 2000).

347 In order to simulate accurately the nutrient concentration dynamics in lakes, interactions between nutrients
348 and other components of the ecosystem are often represented (Asaeda et al., 2001). Nutrient outputs through
349 evaporation, denitrification and rivers or ground outflows can be included, as it is the case of nutrient exter-
350 nal inputs coming from the watershed, the atmospheric deposition, the rainfall, and the ground. Some papers
351 deal specifically with nutrients external loadings that are computed from watershed models such as SPAR-
352 ROW (Benoy et al., 2016; Milstead et al., 2013; Robertson and Saad, 2011), from specific models such as
353 PCLoad (van Puijenbroek et al., 2004) or from satellite images (Politi and Prairie, 2018). In (Liu, 2013), an
354 empirical model is introduced to estimate the nutrient release from industrial manufacturing, livestock breed-
355 ing, crop agriculture, household consumption and atmospheric deposition. Nutrient internal loading is in-

356 creasingly considered in the models (Burger et al., 2008; Li et al., 2015) as its impact on the lake nutrient
357 concentrations and the phytoplankton growth limitation is now recognized (Wu et al., 2017). To simulate the
358 internal cycling it can be necessary to take into account some bio-physical processes such as nutrient upwell-
359 ing fluxes (Hamblin et al., 2003), sediment resuspension (Chung et al., 2009) and nutrient release from sedi-
360 ments (Riverson et al., 2013).

361 **2.4.3 Sediment**

362 About 10% of the references (46 references out of 438) have “sediment” as keyword. Sediment is an impor-
363 tant pool of nutrients that play a key role in the nutrient cycles. Most of the models that specifically focus on
364 sediment are 0D models, namely box-models (Chapra and Canale, 1991) or 1D vertical models (Chung et al.,
365 2009; Gudimov et al., 2016). The main processes considered in these models are: (1) sediment diagenesis
366 which refers to the set of biogeochemical processes within the sediment (Gudimov et al., 2016; Paraska et
367 al., 2014); (2) sediment resuspension (Chung et al., 2009); (3) and nutrient and/or oxygen exchanges between
368 the sediment and the water column (Smits and van der Molen, 1993; Snodgrass, 1987; Walker and
369 Snodgrass, 1986).

370 **2.4.4 Oxygen**

371 The word “oxygen” appears in 46 of the 438 selected references, which represents 10% of the bibliographic
372 corpus. Most of oxygen models are mechanistic (Antonopoulos and Gianniou, 2003; Bell et al., 2006; Bon-
373 net and Poulin, 2004; Chapra and Canale, 1991), but some empirical models have also been developed (Chen
374 and Liu, 2014; Elshaarawi, 1984; Rankovic et al., 2010). Oxygen dynamics is generally modelled by includ-
375 ing one variable, the oxygen concentration, and several related processes. Depending on the other variables
376 of the model, reaeration, aerobic respiration of living organisms, photosynthesis of plants, oxidation of the
377 organic matter and denitrification can be included (Stansbury et al., 2008; Xu and Xu, 2016). Sometimes,
378 sediment oxygen demand (SOD) is also represented (Antonopoulos and Gianniou, 2003; Deus et al., 2013;
379 Terry et al., 2017), to account for the quantity of oxygen uptake by sediment when it is not explicitly repre-
380 sented. In general, oxygen models are coupled with sediment models (Gudimov et al., 2016; Moore et al.,
381 1996).

382 **2.4.5 Cyanobacteria**

383 The keyword “cyanobacteria” has been found in 35 references of the bibliographic corpus, which corre-
384 sponds to 8% of the selected references.

385 According to many authors (*e.g.* Carey et al., 2012; Gkelis et al., 2014; Newcombe et al., 2012; O’Neil et al.,
386 2012), eutrophication and climate change promote algal blooms and more specifically cyanobacterial
387 blooms. Since the 1990s, cyanobacteria has been the subject of modelling works related to eutrophication
388 (Easthope and Howard, 1999; Patterson et al., 1994), but the number of articles devoted to this subject has
389 particularly increased since the mid-2000s. On the 5th of July 2018, the databases available on the Web of
390 Science that we queried with the search equation “TITLE=((lake model*) AND (cyanobacter* OR
391 bloom*))” gave a list of 71 references, more than 85% of which were written after 2005. The models of
392 cyanobacteria range from simple regression models (Onderka, 2007) to 3D coupled hydrodynamic-
393 ecological models (Carraro et al., 2012). Models that are dedicated to the prediction can be mechanistic but
394 are mainly empirical (Carvalho et al., 2011; Cha et al., 2014) and increasingly based on “data-driven” ap-
395 proaches (Obenour et al., 2014; Zhang et al., 2015).

396 Cyanobacteria, which are procaryotic phytoplankton, can be represented either with the same variable as
397 phytoplankton (Shan et al., 2014) - in that case it is assumed to be dominant throughout the year – or as a
398 sub-group of phytoplankton. In CAEDYM model (Hipsey et al., 2011) for example, phytoplankton can be
399 decomposed into five groups: dinoflagellates, cyanobacteria, chlorophytes, cryptophytes and diatoms.
400 Cyanobacteria can also appear under the name of “blue-green algae” as a sub-group of phytoplankton (*e.g.*
401 Harada et al., 2013). Some specific processes of cyanobacteria are sometimes represented, as for example its
402 flotation capacity in the water column (Aparicio Medrano et al., 2013; Walsby, 2005).

403 **2.5 Model selection**

404 The previous paragraphs give an overview of the different types of models that are used for the modelling of
405 lake eutrophication. We can then wonder how to choose among these different types of models. Answering
406 to this question is not simple, but general trends can nevertheless help our choice. The selection of the model
407 type and structure will depend on the available knowledge and data, and on the modelling objective. With
408 little knowledge about the ecosystem, only empirical models can be considered. Regression models can be
409 obtained from few data and are useful to estimate mean annual values. On the other hand, data-driven models
410 based on machine learning techniques require a large amount of data and manage to make short-term predic-

411 tion. On the opposite, process-based models will be considered only if sufficient knowledge about the pro-
412 cesses of the ecosystem is available. Data are nevertheless also required for such models, especially for the
413 calibration of the model parameters. However, the results of process-based models can also be used for
414 qualitative studies. In that case, the model outputs are validated by confrontation with the already acquired
415 knowledge. Finally, when both knowledge and data are available, we can consider mixed approaches. For
416 example, we can use a Kalman filter technique that requires data to adjust the parameters of a process-based
417 model. Concerning the structure of the model, the variables to be represented are the variables of interest for
418 the study, namely the variables that we want to simulate and the variables on which they depend. In the same
419 way, we will represent the processes of interest and the ones that we assume to have an impact on the system
420 we intend to represent. The time-scale of the targeted simulations will also determine the processes to be
421 included. For example, it may be useless to take into account daily variations of some processes if we are
422 interested on the annual variations of the ecosystem. Finally, depending on the level of ecological description
423 (individuals, species, populations, etc.), different types of models can be considered: individual based-
424 models, population equations, meta-ecosystems.

425 **3 Main results obtained with process-based models**

426 In the sequel, we only review the results obtained with process-based models because this type of models is
427 required when models are to be used in prospective scenarios. Indeed, for assessing ecosystem evolution, at
428 long or mid-term, in response to local and global changes (e.g. climate change, urbanization, ...) or restora-
429 tion actions, it is mandatory in our opinion that the main processes involved in the ecosystem functioning are
430 taken into account.

431 Many eutrophication models of lake ecosystems have been applied to study sites for which monitoring data
432 are available. Model description, including represented processes and equations, as well as calibration and
433 validation results are presented in many articles (e.g. Bruce et al., 2006; Elliott and Thackeray, 2004; Elliott
434 et al., 2007; Hamilton and Schladow, 1997; Leon et al., 2011; Lewis et al., 2002; Los and Brinkman, 1988;
435 Reynolds et al., 2001, 2001; Riley and Stefan, 1988, 1988; Rukhovets et al., 2003). These models are mainly
436 applied to simulate phytoplankton biomass, nutrients, oxygen, and in some cases cyanobacteria. The results
437 of these models are given in the sequel.

438

439 **3.1 Phytoplankton dynamics**

440 Aimed at better understanding phytoplankton dynamics, process-based models are run at seasonal to mul-
441 tiannual time scales. The main issues addressed are as follows: biomass of the main phytoplankton groups
442 and/or of total phytoplankton, total chlorophyll concentration, values at different depths or mean values in
443 the epilimnion, phenology of phytoplankton blooms (biomass peak dates, duration of threshold overpass),
444 etc.

445 Phytoplankton data are generally biovolumes of species identified by microscopy. Because of the long time
446 necessary to obtain this type of data, the measurements are frequently performed in mean samples, for exam-
447 ple collected in the euphotic layer or at a specific depth (Bruce et al., 2006; Elliott et al., 2007). Chlorophyll
448 is frequently considered as a proxy of phytoplankton biomass. For example, the results of multiannual simu-
449 lations over 11 years in Lake Erken (Sweden) are expressed as monthly mean total chlorophyll in the surface
450 layer (0-10m) (Elliott et al., 2007).

451 In large lakes, 3D modelling can be required. Hillmer et al. (2008) compare the results of 1D vertical
452 (DYRESM-CAEDYM) and 3D (ELCOM-CAEDYM) models on the same study site, Lake Kinneret. Taking
453 into account the horizontal heterogeneity of the lake makes it possible to obtain better results. In Lake Erie
454 (Leon et al., 2011) mesoscale physical processes such as upwelling and general circulation in the lake have
455 been modelled with the 3D ELCOM model. The spatio-temporal evolution of the variables is well simulated
456 even if the authors underline the difficulty of comparing the simulation results of the phytoplankton succes-
457 sion with the measurements because of the necessary aggregation of the species in the model.

458 Concentrations of chlorophyll or carbon are derived from field measurements of biovolumes, by using con-
459 version factors, which vary widely between authors. The quality of the phytoplankton biomass results, when
460 evaluated in relation to the total chlorophyll concentration, is generally considered satisfactory. To judge the
461 acceptability of the results, one criterion frequently used, is that the model results remain within a range of
462 two standard deviations from the mean of the measured values (Elliott et al., 2007).

463 Functional traits have been introduced in the definition of phytoplankton groups in order to better model the
464 functional characteristics of an ecosystem and its responses to changes in nutrient inputs (Mieleitner and
465 Reichert, 2008). This should also make the model more generic and allow better portability to other study

466 sites. Nevertheless the predictive capacity of these models remains modest. The ability of 124 models to
467 replicate the dynamics of functional phytoplankton groups has been studied recently (Shimoda and Arhondit-
468 sis, 2016). The authors note a very large variability in the characterization of the functional phytoplankton
469 groups as well as in the mathematical formulations that describe the main physiological processes of these
470 groups (growth, nutrient absorption kinetics, mobility, etc.).

471

472 **3.2 Cyanobacteria dynamics**

473 Cyanobacteria strongly impair lake ecological functioning. Moreover they cause significant public health
474 problems. Modelling their dynamics and the processes that control them are therefore the subject of many
475 studies (Belov and Giles, 1997; Carraro et al., 2012; Elliott, 2012; Guven and Howard, 2006; Hense and
476 Beckmann, 2006). According to many authors (*e.g.* Carey et al., 2012; Gkelis and Zaoutsos, 2014; New-
477 combe, 2012; O’Neil et al., 2012; Paerl and Huisman, 2008; Paerl and Paul, 2012), the ongoing climate
478 change is likely to result in an increase in global cyanobacterial biomass as well as in occurrences of blooms.
479 Guven and Howard (2006) provide a review and critical analysis of 12 main models of cyanobacteria devel-
480 opment in lake ecosystems. Two modelling approaches are discussed: deterministic models and neural net-
481 work models. These models generally focus on describing either the biological processes involved in the
482 growth of biomass or the processes involved in the motion of cells. Few people combine all the aspects that
483 affect the dynamics of cyanobacteria.

484 Migration in the water column is a characteristic process of cyanobacteria: the rate of settling or flotation in
485 the water column varies according to their density, which itself varies according to the amount of carbohy-
486 drates and volume of vacuoles in the cells. This is a very complex, non-linear process, with many feedbacks.
487 It involves the intensity of photosynthesis, which is itself a function of the intensity of light in the water col-
488 umn, and therefore of the location of cyanobacteria in the water column. In addition, the different species of
489 cyanobacteria form colonies whose morphometric characteristics affect the mobility. The models depict the
490 migration process with different levels of complexity.

491 In Kromkamp and Walsby (1990), the density change depends on two simultaneous processes: an increase
492 controlled by the light intensity received by the cells and a decrease as a function of time. The parameter

493 values of the equations were obtained from experimental data of density change of a cyanobacterium species
494 (*Planktothrix aghardii*) as a function of time and light intensity. The results show that the size of the colonies
495 influences the migration rate but not the depth reached in the water column. The biomass vertical location
496 fluctuates according to the rise of the floating colonies and the settling of others towards the bottom. Phos-
497 phorus deficient cells migrate to greater depths than light-limited cells.

498 Howard et al. (1996) propose a cyanobacterial growth and transport model that accounts for, on the one
499 hand, the photosynthesis production, the cell density variation and the vertical migration of cells and on the
500 other hand, the turbulent mixing in the water column that also affects cyanobacteria motion.

501 Belov and Giles (1997) present a dynamic model of cyanobacteria motion based on the properties of regula-
502 tion of cell buoyancy under simplified conditions: an isothermal water column where nutrients are not limit-
503 ing factors. The main factor controlling cell mobility is the nycthemeral cycle of light. The article focuses on
504 analysing under these conditions the mathematical behaviour of the equations involved in the model.

505 One of the specificities of cyanobacteria is the ability of certain species, the diazotrophic species, to fix at-
506 mospheric nitrogen. Accounting for this process allows the models to better represent the control of the suc-
507 cession of species by the available nutrients. Hense and Beckmann (2010) propose several versions of a
508 model of the life cycle of diazotrophic cyanobacteria, considering the active phase of nitrogen fixation and
509 the vegetative phase of cells. The ecological characteristics, life cycle of cyanobacteria and interactions with
510 hydrodynamics are particularly complex (Figure 2). The simplified approach satisfactorily describes the dy-
511 namics of cyanobacteria, in particular the time patterns of blooms and the intensity of nitrogen fixation. The
512 proposed set of equations can be inserted into different types of lake models of cyanobacterial dynamics.

513

514 **Figure 2. General sketch of main steps of cyanobacteria life cycle (Hense, 2010).**

515

516 In Lake Pusiano, Carraro et al. (2012) validated the 3D model ELCOM coupled to the CAEDYM biological
517 model with high frequency measurements to identify the factors, including hydrodynamic factors, which
518 drive the spatial distribution of the cyanobacterium *P. rubescens*.

519 Regarding the impact of climate change on cyanobacteria, Elliott (2012) reviewed different predictive mod-
520 els. Most of the analysed results show an increase in the relative biomass of cyanobacteria due to an increase
521 in water temperature, an increase in residence time and an increase in nutrient loading from the watershed.
522 The main effect of climate change is to alter the phenology of cyanobacterial blooms and the abundance of
523 their biomass. The lake food web is also changing due to the low nutritional value of cyanobacteria for zoo-
524 plankton.

525

526 **3.3 Integration of models in early warning system**

527 For management applications, models are often integrated into warning systems to predict short-term phyto-
528 plankton blooms, particularly to improve operational control of cyanobacterial blooms (Shimoda and Arhon-
529 ditsis, 2016). Most articles describe the models used and the architecture of the system. But few *a posteriori*
530 comparisons of the forecasts with measurements made afterwards, are performed.

531 In order to predict algal blooms in Lake Taihu, the EcoTaihu model has been integrated into a Windows
532 software platform (Zhang et al., 2013). The results of the simulations generally show a good agreement with
533 the measurements. But the authors also point out that no model is able to integrate all ecological processes.
534 The forecast discrepancies are not only due to the model but also to data uncertainties and because modelling
535 results and field measurements are not directly comparable.

536

537 **3.4 Ecosystem response to local management strategies**

538 Eutrophication models can be used to study prospective scenarios and compare the impact of local manage-
539 ment alternatives. Several management scenarios of Los Molinos reservoir (Argentina) were tested with a
540 model describing the dynamics of nutrients and phytoplankton (Rodriguez Reartes et al., 2016). After cali-
541 bration and validation of the model, scenario simulation results highlighted the impact on water quality of
542 livestock husbandry practices and of insufficient wastewater treatment, especially septic tanks. According to
543 the model simulations, the combination of wastewater treatment in the reservoir direct watershed and meas-
544 ures to reduce nutrient loading (N and P) from livestock would be the most beneficial to preserve the quality
545 of the lake.

546 The effects of different actions to reduce eutrophication of a lake in Sweden (reduction of nutrient inputs,
547 biomanipulation, herbicide application) were analysed with a vertical 1D biogeochemical model (Pers,
548 2005). According to the simulation results, the best effects are obtained with a nutrient reduction and bioma-
549 nipulation of the fish species.

550 The comparison of different prospective scenarios should include a reference scenario. This is not the case in
551 most of the performed modelling studies. This is due to the lack of sufficiently long-term historical data sets.
552 Moreover, it is particularly complex to achieve a reliable assessment of the environmental conditions prior to
553 the onset of eutrophication. For total phosphorus, reference values of the watershed loading can be estimated
554 by different approaches (export coefficients, morpho-edaphic indices, paleolimnological estimates). But the
555 results of these different methods have rarely been compared. A study performed on 35 sub-alpine lakes in
556 northern Italy (Salerno et al., 2014) highlighted the need of deterministic watershed models to estimate the
557 total reference phosphorus inputs.

558 An expected outcome of the prospective simulations regards the level of nutrient loading by the watershed
559 that must not be overpassed to avoid eutrophication of a lake. But even when the targets to be achieved are
560 derived from modelling results, the authors remind that these values must be considered with caution as the
561 models are not able to anticipate accurately the changes in the trophic web that would occur in response to
562 nutrient reduction (*e.g.* Trolle et al., 2008).

563 Modelling studies mainly focus on the advantages of the modelling approach developed and its transferabil-
564 ity to other systems. The model is generally implemented on a particular study site for which a sufficient data
565 set exists. Despite the transferability of process-based models, they must be implemented in a configuration
566 adapted to the characteristics of each lake in order to estimate the required threshold of nutrient loading
567 (Trolle et al., 2008). Moreover, due to the complexity of the ecological functioning of lake ecosystems, many
568 processes are not taken into account or are very simplified in the models (role of sediment, change of phyto-
569 plankton assemblages, mobility of certain species, etc.). When recommendations are made, the authors are
570 very cautious and they immediately nuanced the recommendations. Thus, the total phosphorus loading which
571 would allow Lake Ravn (Denmark) to achieve the objectives of good ecological status required by the Euro-
572 pean Framework Directive on Water, was estimated thanks to a vertical 1D model (Trolle et al., 2008). The
573 authors recommend a reduction of at least 50% of the total phosphorus inputs by the watershed. In parallel,

574 they raise awareness on the possible cascade effects within the food web, not simulated by the model, and
575 which could lead to an unpredictable evolution of the ecosystem.

576

577 **3.5 Ecosystem response to global changes**

578 A common application of models is the study of expected effect of global changes, especially climate
579 change. Climate change will impact precipitation patterns, wind speeds, solar radiation, and air temperature
580 (*e.g.* Arnell and Gosling, 2013; Beniston et al., 2007; European Environment Agency, 2012). Most models
581 simulate the effect of climate change on different aspects of lake functioning related to eutrophication:
582 mainly oxygen concentrations (Fang and Stefan, 1997, 2009), phytoplankton growth (Hassan et al., 1998)
583 and the dominance of cyanobacteria (*e.g.* Elliott, 2012). The consideration of climate change is mainly based
584 on two approaches: (1) the use of outputs from regional climate models treated by downscaling techniques to
585 obtain meteorological forcing at the studied lake level; or (2) a meteorological forcing sensitivity analysis
586 where actual measured meteorological data are modified by a range of factors.

587 Very often the analysis of the influence of climate change, in particular of global warming, focuses on
588 cyanobacteria. Global warming is supposed to have a positive effect on the increase of cyanobacteria bio-
589 mass (*e.g.* Carey et al., 2012; Newcombe, 2012; Paerl and Paul, 2012; Posch et al., 2012; Wagner and
590 Adrian, 2009). Nevertheless, very few reliable predictive simulations of the dominance of cyanobacteria
591 have still been performed (Elliott, 2012).

592 In Lake Windermere (Great Britain), the effect of an increase in water temperature and phosphorus loading
593 on phytoplankton has been studied with the PROTECH model (Elliott, 2011). The results show an earlier
594 spring peak of diatoms (2-3 days/°C). The biomass of diatoms, which is controlled mainly by light is little
595 changed. On the other hand, the biomass of cyanobacteria increases with the increase of the two factors stud-
596 ied. These two factors act in synergy, the predominant influence being due to phosphorus inputs. The domi-
597 nance of cyanobacteria is enhanced in late summer. Temperature impacts mainly succession and seasonal
598 phytoplankton community whereas nutrient inputs affect the amount of produced biomass.

599 Howard and Easthope (2002) used the predictions of the HADCM2 climate model over a period of 90 years,
600 until the end of the 21st century, to simulate the evolution of the growth of the cyanobacterium *Microcystis*

601 in Farmoor Lake (Great Britain). The main meteorological variables used are the monthly averages of wind
602 speed, cloud cover and solar radiation. The results do not show an overall increase in the annual biomass of
603 cyanobacteria. On the other hand, the growth period of cyanobacteria would be longer with higher biomass
604 than currently in spring (May) and autumn (September). These results only quantify the direct effect of cli-
605 mate change because the long-term change in rainfall on loading from the watershed is not taken into ac-
606 count.

607 The effect of global warming predicted until the end of the 21st century has been studied in three lakes in
608 New Zealand (Trolle et al., 2011b). A regional climate model based on the IPCC A2 scenario predicts an
609 average annual increase in air temperature of about 2.5 ° C in the 2100s in the studied lake region. The future
610 climate conditions are described in a very simplified way; only the change of air temperature is taken into
611 account. The average annual increase in air temperature forecast for the year 2100 has been added to the
612 average daily temperatures over the period 2002-2007. The morphometric and trophic characteristics of the
613 three modelled lakes are different. The first is quite deep (33.5m) and oligo-mesotrophic, the second shallow
614 (13.5m) and eutrophic and the third very shallow (2.5m) and very eutrophic. Cyanobacteria are present only
615 in the second lake. Modelling results show an increase in phytoplankton biomass in summer and an increase
616 in the dominance of cyanobacteria in the second lake. The average annual biomass increases in the oligo-
617 mesotrophic and eutrophic lakes but decreases in the highly eutrophic lake. The phytoplankton biomass de-
618 creases in winter and spring, especially diatoms.

619 A recent analysis of ten modelling studies (Elliott, 2012) on the impact of climate change on cyanobacteria
620 has shown an increase in the relative abundance of cyanobacteria with an increase in water temperature, an
621 increase in the residence time of the water and an increase in nutrient loading by the catchment.

622 The direct effects of climate change mainly relate to phenology of phytoplankton dynamics but little to the
623 annual amount of total biomass. These changes in phytoplankton succession may result in nitrogen limitation
624 in some lakes, and thus favour the dominance of nitrogen-fixing cyanobacteria. In addition, warmer water in
625 spring can increase nutrient uptake by the phytoplankton community, which in some lakes causes nitrogen
626 limitation later in the year, potentially favourable for some nitrogen-fixing cyanobacteria. The increase in the
627 relative abundance of cyanobacteria may also impact the higher levels of the ecosystem food web due to the
628 low grazing of cyanobacteria by zooplankton.

629 **3.6 Coupled models of lake and watershed**

630 Coupling watershed modelling and lake response modelling is a key issue for an efficient use of models in
631 eutrophication control. But to our knowledge, few research results are still available.

632 Most often, the coupling between watershed model and lake model is not effective. A hydrological model of
633 Lake Cayuga watershed (USA) has provided estimates of nutrient loading by lake tributaries (Haith et al.,
634 2012). But this watershed model is not coupled with a model of the lake itself. This is also the case for Lake
635 Gucheng watershed in China (Huang et al., 2009) or for Lake Tahoe watershed (USA) (Riverson et al.,
636 2013).

637 Since the 2000s, integrated modelling of the watershed and the lake has been undertaken. Lake watershed
638 modelling is conducted with the objective of providing the lake model with input data to then simulate the
639 lake response to watershed loadings. But the limits of these coupled models come from the cumulative un-
640 certainties of the hydrological model and the lake model. If the inflows are fairly well simulated, the main
641 uncertainties are due to errors in computing nutrient concentrations in the lake tributaries (Liu et al., 2006;
642 Silva et al., 2016; van Puijenbroek et al., 2004).

643 Carraro et al. (2012b) propose for Lake Pusiano (Northern Italy) a coupled model of loading by the water-
644 shed (SWAT model) and a deterministic model of the lake response (DYRESM-CAEDYM model). The
645 results obtained for different scenarios are discussed and compared, but no quantified recommendation for a
646 percentage of reduction in loadings or concentrations to be achieved is given.

647 Very few studies have focused on coupling climate, watershed and lake models. To study phytoplankton
648 biomass in a large shallow lake, Lake Malaren (Sweden), a regional climate model, a hydrological model,
649 and a lake model were used in sequence (Markensten et al., 2010). In this lake, warming increases the dura-
650 tion of phytoplankton production, slightly increases total biomass, and modifies the phytoplankton composi-
651 tion to the advantage of nitrogen-fixing cyanobacteria. According to the authors, the change in the hydro-
652 logical regime and therefore the nutrient loading to the lake drives the dominance of cyanobacteria.

653 The aquatic continuum, from headwaters to the ocean, is at the heart of current research on biogeochemical
654 processes in inland waters. This is reflected in the topic of the special issue of *Limnology and Oceanography*,
655 a reference journal in the field, entitled "Headwaters to oceans: ecological and biogeochemical contrasts

656 across the aquatic continuum" (Xenopoulos et al., 2017). In this area, progress on knowledge integration is
657 rapid and modelling of the continuum, still in its infancy, should make significant progress in the coming
658 years.

659

660 **4 Discussion and perspectives**

661 The development of lake eutrophication models is still a growing field in limnology. However several au-
662 thors complain that the performances of the biological models remain relatively low (Mooij et al., 2010;
663 Shimoda and Arhonditsis, 2016). According to Trolle et al., (2011a), the problem is not the "lack of knowl-
664 edge about ecosystem functioning, but rather the limited extent of open communication, inadequate collabo-
665 ration and lack of suitable structure to support the aquatic scientific modelling community". In their paper,
666 these authors argue for the adoption of good practices for developing, using and sharing models effectively
667 and correctly, which should help improving the models. Mooij et al. (2010) identified two challenges for
668 making further progress in lake ecosystem modelling: to avoid developing more models largely following
669 the concept of others ('reinventing the wheel') and to avoid focusing on only one type of model, while ignor-
670 ing new and diverse approaches that have become available ('having tunnel vision')" (Mooij et al., 2010a).
671 This suggests to merge different modelling approaches, such as 1D hydrodynamic-ecological model and
672 super individual-based model (Makler-Pick et al., 2011), or machine learning models and physical dynamical
673 models (Crisci et al., 2017).

674 To improve the models, the complexity of the predictive ecosystem models should also be increased, because
675 "there is a lot of knowledge that we are not using" (Hellweger, 2017). The most striking example is the al-
676 most systematic use of the Monod function for representing the growth of a phytoplankton population
677 whereas the use of internal (vs. external) nutrient quota (Droop, 1968) could be represented (Hellweger,
678 2017). Another example is the use of Michaelis-Menten kinetics for nutrient uptake by phytoplankton, which
679 does not enable to represent the variable stoichiometry of biomass and of nutrient uptake (Flynn, 2010, 2005;
680 Smith et al., 2014) whereas size- and trait-based kinetics give promising results (Fiksen et al., 2013; Smith et
681 al., 2014). In the same way, the process of mineralization of the organic matter by bacteria, which has been
682 proved to be important for the cyanobacteria dynamics, is often represented as a simple chemical reaction
683 with a rate either constant or dependent on the bacteria concentration at best (Li et al., 2014). Xu et al. (2015)

684 also claim that the use of more advanced statistical methods, such a quantile regression, can improve the
685 models of lake eutrophication.

686 Even if the relationship between complexity and uncertainty of models is not so clear (Håkanson, 1995;
687 Hellweger, 2017; Jørgensen, 1990), it is obvious that the outcomes of simulated scenarios are limited by
688 great uncertainty (Arhonditsis and Brett, 2004). Some authors have attempted to quantify model errors due to
689 uncertainty (Bennett et al., 2013; Hongping and Yong, 2003; Reckhow, 1994; Scavia et al., 1981; Snodgrass,
690 1985; Stow et al., 1997; Van Straten and Keesman, 1991), but few models include thorough uncertainty
691 analyses (Hongping and Yong, 2003).

692 This uncertainty partly comes from the large set of parameters (sometimes more than 100) to be calibrated.
693 To quantify the effect of parameter uncertainties on the model outputs, sensitivity analysis can be conducted
694 (Arhonditsis et al., 2007; Brett et al., 2016; Janse et al., 2010; Yi et al., 2016). However, as for general uncer-
695 tainty analysis, sensitivity analysis is not always performed. Two articles (Arhonditsis and Brett, 2004; Shi-
696 moda and Arhonditsis, 2016) have investigated whether the conventional methodological procedures for
697 sensitivity analysis, calibration and validation, are reported in the papers or not. They show that only half of
698 the papers present sensitivity analysis results and that “manual” or “trial and error” calibration is the most
699 applied calibration procedure. Very few papers use automatic calibration procedures that are either based on
700 optimization or on Monte Carlo and Bayesian inference. Moreover these papers only deal with 0D or 1D
701 models.

702 Another part of output uncertainty comes from the model structure itself. To reduce it, several “ensemble
703 approaches” have been proposed, similar to those used for weather forecasts. In (Gal et al., 2014; Nielsen et
704 al., 2014) an ensemble of model runs obtained with several “equivalent” set of parameters are used to im-
705 prove the model predictive power. In (Trolle et al., 2014), the same scenario is simulated using an ensemble
706 of models. Bayesian model averaging (BMA) can also be used to improve the predictive performance of the
707 models (Hamilton et al., 2009).

708 Another effective way is to conduct cross-comparisons of similar models on the same study sites. This type
709 of comparative studies has been performed recently for 1D models (Bruce et al., 2018; Perroud et al., 2009;
710 Stepanenko et al., 2012, 2010). To our knowledge very few attempts have been made for hydrodynamic-
711 ecological models (Trolle et al., 2014) and none for 3D models.

712 Nevertheless, to perform such studies, portability of the model software is required. This type of concern is
713 just starting to be addressed by the modeller community. A Fortran-based Framework for Aquatic Biogeo-
714 chemical Models (FABM - Bruggeman and Bolding, 2014; Trolle et al., 2011) enables to easily couple hy-
715 drodynamic models with ecological models, whereas the project “Framework for Interoperable Freshwater
716 Models” (FIFM) has investigated flexible computer-based frameworks for integrating freshwater models
717 (Elliott et al., 2014). The Database Approach To Modelling (DATM -Mooij et al., 2014) enables to auto-
718 matically implement the same model under different frameworks. In order to facilitate the comparison of
719 models or the application of one model on several lakes, it is also necessary to share the codes and the data
720 sets (Mooij et al., 2010a). Just as importantly, the datasets must be of good quality and enriched with meta-
721 information (such as the type of sensor used and their accuracy). This is mandatory for the good interpreta-
722 tion and use of the data (Mooij et al., 2010a). The use of high-frequency sensors (Brentrup et al., 2016; Car-
723 raro et al., 2012; Soullignac et al., 2017), as well as satellite images (Curtarelli et al., 2015; Dash et al., 2011;
724 Tyler et al., 2006; Yacobi, 2006), will also enrich significantly the data sets. Using such enriched and good-
725 quality data sets can improve the model performances. Indeed, the more data we use for calibration, com-
726 parison with model outputs or to feed machine learning models, the greater the accuracy of the model will
727 be.

728

729 **5 Conclusion**

730 Early lake eutrophication models in the 1970s were empirical models linking in-lake phosphorus and chlo-
731 rophyll concentrations, as well as models of watershed nutrient loading and in-lake chlorophyll concentra-
732 tion. These models, very easy to implement, were useful for providing targets of nutrient and chlorophyll
733 concentrations, required for reducing or controlling lake eutrophication. Dynamic deterministic models have
734 been then developed, whose characteristics are very diverse as regards the spatial dimension (well-mixed
735 system, 1D vertical to 3D models), the sediment exchange with the water column, the complexity of ecologi-
736 cal functioning and the hydrodynamics. Most of these models represent the pelagic zone of the lake. The
737 most represented state variables include phytoplankton, considered as a single group or divided into main
738 groups, nutrients (phosphorus and nitrogen) and oxygen. Among the phytoplankton groups, cyanobacteria
739 have been increasingly represented since the mid-2000s. The dynamics of macrophytes and their possible

740 competition with phytoplankton are accounted for in some rather recent models. One notable development
741 over the past decade has been the modelling of phytoplankton dynamics based on the functional traits of
742 dominant species. The objectives of the modelling studies are frequently related to the assessment of the
743 expected mid-and long-term evolution of lake eutrophication under the influence of global changes (nutri-
744 ents, urbanization, climate...). Among these changes, the effects of global warming are the most frequently
745 addressed. At these time scales, a main barrier that models have to face, regards the evolution of the phyto-
746 plankton succession and its cascading effects on lake ecological functioning. Recent evolutions show a
747 strong coupling between modelling and acquisition of new types of experimental data (remote sensing, high
748 frequency field sensors, biology molecular data...). A strong trend seen in papers published in the last dec-
749 ade is the increasing number of application of 3D models coupled with satellite images of phytoplankton
750 biomass spatial distribution.

751 **6 Appendix**

752 In this appendix, we first give some details about the method applied for obtaining the bibliographic corpus
753 considered in this review. We then present some simple statistics about: (1) the number of publications and
754 citations; (2) the general categories, research areas and journal titles; (3) the keywords of the references in-
755 cluded in the bibliographic corpus.

756 **6.1 Selection of the bibliographic corpus**

757 The present review was performed, using the bibliographic search tool proposed by Web of Science. The
758 first database search of February 2017 (Crave et al., 2017) was updated on 1st June 2018 with the following
759 search equation:

```
760 TITLE=((eutrophic* OR oxygen* OR hypox* OR anox* OR phytoplankton* OR "harmful alga"* OR nutri-  
761 ent* OR cyanobact* OR proliferat*) AND (model* OR numerical* OR simulat*) AND (lake* OR reser-  
762 voir*))
```

763 All citation databases were consulted for all available years (from 1956 to 2018). Among the references ob-
764 tained, we kept only the journal articles written in English. This query provided us with a list of 487 refer-
765 ences from which we removed 49 references that were not relevant. We finally get a bibliographic corpus of
766 438 references among which 431 references are indexed in the Web of Science core collection, 62 in the

767 MEDLINE database, 1 in the KCI Korean Journal Database and 1 in the Scientific Electronic Library Online
768 (SCIELO) database. Each reference may be indexed in several databases.

769 **6.2 Number of publications and citations**

770 The first referenced paper (Droop, 1968) was published in 1968. Since then, the number of publications per
771 year has obviously increased (Figure 3), following the global tendency observed for the total number of sci-
772 entific publications. In average, 8.6 articles were published per year, and each article was cited 17 times. The
773 total number of citations is 7447, which corresponds, since 1968, to a mean value of 146 citations per year.

774 **Figure 3. Number of publications and citations per year, based on the ISI Web of Science citation report.**

775

776 **6.3 General categories, research areas and journal titles**

777 The repartition of the references are given in terms of general categories, research areas and journal titles
778 (Table 2). We note that most of the references of the bibliographic corpus come from the “science technol-
779 ogy” and “life sciences biomedicine” categories. This shows that the studies are motivated both by academic
780 objectives to improve knowledge and by more applied objectives to develop management strategies (see
781 section 2.2). One third of the references (respectively one quarter) also belongs to the category of “physical
782 sciences” (respectively "technologies"), knowing that one reference may belong to several categories.

783 The repartition according to the research areas shows that lake eutrophication modelling is a multi-
784 disciplinary field of research. Most of the references (two thirds) are in the field of “environmental sciences
785 and ecology”, but the research areas of “marine and freshwater biology”, “water resources” and “engineer-
786 ing” also contain a significant number of references (from 20 to 30%). Note that some publications in
787 “mathematics” and “computer science” are also included in the bibliographic corpus, which is not surprising
788 as we focus on modelling studies.

789 The journal in which most papers (16%) have been published is “Ecological modelling”, perhaps because it
790 is one of the few journals in environmental sciences that only focus on modelling. The scope of the other
791 most represented journals cover the research area of water sciences in general, without restriction to model-
792 ling approaches.

793

794 **Table 2. Repartition of the publications according to their general categories, their research areas and the journal title (pro-**
795 **vided by Web of Science). Only the research areas (respectively the journal titles) that represent more than 2% (respectively**
796 **1.5%) of the bibliographic corpus are listed.**

797

798 **6.4 Keywords**

799 An automatic search routine was implemented to sort the keywords according to the number of publications
800 in which they appear. The routine does not search for an exact match but for an inclusion. For example, a
801 publication with "lake models" as keyword will be counted for the keywords "lake model", "models",
802 "model" and "lake". Only the keywords that appear in more than 20 publications of the bibliographic corpus
803 have been considered. The obtained sorted list has then been divided in sub-groups as presented in Table 3.
804 Not surprisingly, the most common keywords are “lake”, “water” and “eutrophic”.

805 This classification of the keywords give an interesting overview of the research works presented in the ana-
806 lysed bibliographic corpus. Each sub-group will be discussed more in details in the following sections.

807

808 **Table 3. Classification of keywords according to the number of publications in which they appear.**

809

810 **7 Acknowledgements**

811 This review was prepared within the framework of the joint scientific appraisal (ESCo) on eutrophication
812 requested by the French ministries of the environment and agriculture and the French Agency for Biodiver-
813 sity (AFB). The authors thank the ESCo steering committee for this great opportunity to write this review on
814 lake eutrophication modelling. The authors also acknowledge the French Research Agency for funding the
815 ANSWER project (ANR-16-CE32-0009). A detailed analysis of the existing process-based models was con-
816 ducted by the authors within this French-Chinese Research Project that focuses on eutrophic lake ecosystem
817 modelling to study the impact of anthropogenic environmental changes on the proliferation of cyanobacteria.

818

819 **8 References**

- 820 Afshar, A., Saadatpour, M., Marino, M.A., 2012. Development of a Complex System Dynamic Eutrophica-
821 tion Model: Application to Karkheh Reservoir. *Environ. Eng. Sci.* 29, 373–385.
822 <https://doi.org/10.1089/ees.2010.0203>
- 823 Alonso Fernandez, J.R., Garcia Nieto, P.J., Diaz Muniz, C., Alvarez Anton, J.C., 2014. Modeling eutrophica-
824 tion and risk prevention in a reservoir in the Northwest of Spain by using multivariate adaptive re-
825 gression splines analysis. *Ecol. Eng.* 68, 80–89. <https://doi.org/10.1016/j.ecoleng.2014.03.094>
- 826 Anagnostou, E., Gianni, A., Zacharias, I., 2017. Ecological modeling and eutrophication-A review. *Nat.*
827 *Resour. Model.* 30, e12130. <https://doi.org/10.1111/nrm.12130>
- 828 Anderson, D.M., Cembella, A.D., Hallegraeff, G.M., 2012. Progress in Understanding Harmful Algal
829 Blooms: Paradigm Shifts and New Technologies for Research, Monitoring, and Management. *Annu.*
830 *Rev. Mar. Sci.* 4, 143–176. <https://doi.org/10.1146/annurev-marine-120308-081121>
- 831 Antonopoulos, V.Z., Gianniou, S.K., 2003. Simulation of water temperature and dissolved oxygen distribu-
832 tion in Lake Vegoritis, Greece. *Ecol. Model.* 160, 39–53. [https://doi.org/10.1016/S0304-3800\(02\)00286-7](https://doi.org/10.1016/S0304-3800(02)00286-7)
- 834 Aparicio Medrano, E., Uittenbogaard, R.E., Dionisio Pires, L.M., van de Wiel, B.J.H., Clercx, H.J.H., 2013.
835 Coupling hydrodynamics and buoyancy regulation in *Microcystis aeruginosa* for its vertical distribu-
836 tion in lakes. *Ecol. Model.* 248, 41–56. <https://doi.org/10.1016/j.ecolmodel.2012.08.029>
- 837 Arhonditsis, G., Brett, M., 2004. Evaluation of the current state of mechanistic aquatic biogeochemical mod-
838 eling. *Mar. Ecol. Prog. Ser.* 271, 13–26. <https://doi.org/10.3354/meps271013>
- 839 Arhonditsis, G.B., Qian, S.S., Stow, C.A., Lamon, E.C., Reckhow, K.H., 2007. Eutrophication risk assess-
840 ment using Bayesian calibration of process-based models: Application to a mesotrophic lake. *Ecol.*
841 *Model.* 208, 215–229. <https://doi.org/10.1016/j.ecolmodel.2007.05.020>
- 842 Arnell, N.W., Gosling, S.N., 2013. The impacts of climate change on river flow regimes at the global scale.
843 *J. Hydrol.* 486, 351–364. <https://doi.org/10.1016/j.jhydrol.2013.02.010>
- 844 Asaeda, T., Trung, V.K., Manatunge, J., 2000. Modeling the effects of macrophyte growth and decomposi-
845 tion on the nutrient budget in Shallow Lakes. *Aquat. Bot.* 68, 217–237.
846 [https://doi.org/10.1016/S0304-3770\(00\)00123-6](https://doi.org/10.1016/S0304-3770(00)00123-6)

847 Asaeda, T., Trung, V.K., Manatunge, J., Van Bon, T., 2001. Modelling macrophyte-nutrient-phytoplankton
848 interactions in shallow eutrophic lakes and the evaluation of environmental impacts. *Ecol. Eng.* 16,
849 341–357. [https://doi.org/10.1016/S0925-8574\(00\)00120-8](https://doi.org/10.1016/S0925-8574(00)00120-8)

850 Asaeda, T., Van Bon, T., 1997. Modelling the effects of macrophytes on algal blooming in eutrophic shallow
851 lakes. *Ecol. Model.* 104, 261–287. [https://doi.org/10.1016/S0304-3800\(97\)00129-4](https://doi.org/10.1016/S0304-3800(97)00129-4)

852 Bartram, J., Carmichael, W., Chorus, I., Jones, G., Skulberg, O., 1999. Introduction, in: *Toxic Cyanobacteria*
853 *in Water*. Chorus I. and Bartram J., London and New York.

854 Bell, V.A., George, D.G., Moore, R.J., Parker, J., 2006. Using a 1-D mixing model to simulate the vertical
855 flux of heat and oxygen in a lake subject to episodic mixing. *Ecol. Model.* 190, 41–54.
856 <https://doi.org/10.1016/j.ecolmodel.2005.02.025>

857 Belov, A.P., Giles, J.D., 1997. Dynamical model of buoyant cyanobacteria 11.

858 Beniston, M., Stephenson, D.B., Christensen, O.B., Ferro, C.A.T., Frei, C., Goyette, S., Halsnaes, K., Holt,
859 T., Jylhä, K., Koffi, B., Palutikof, J., Schöll, R., Semmler, T., Woth, K., 2007. Future extreme events
860 in European climate: an exploration of regional climate model projections. *Clim. Change* 81, 71–95.
861 <https://doi.org/10.1007/s10584-006-9226-z>

862 Bennett, N.D., Croke, B.F.W., Guariso, G., Guillaume, J.H.A., Hamilton, S.H., Jakeman, A.J., Marsili-
863 Libelli, S., Newham, L.T.H., Norton, J.P., Perrin, C., Pierce, S.A., Robson, B., Seppelt, R., Voinov,
864 A.A., Fath, B.D., Andreassian, V., 2013. Characterising performance of environmental models. *En-
865 viron. Model. Softw.* 40, 1–20. <https://doi.org/10.1016/j.envsoft.2012.09.011>

866 Benoy, G.A., Jenkinson, R.W., Robertson, D.M., Saad, D.A., 2016. Nutrient delivery to Lake Winnipeg from
867 the RedAssiniboine River Basin - A binational application of the SPARROW model. *Can. WATER
868 Resour. J.* 41, 429–447. <https://doi.org/10.1080/07011784.2016.1178601>

869 Bernhardt, J., Elliott, J.A., Jones, I.D., 2008. Modelling the effects on phytoplankton communities of chang-
870 ing mixed depth and background extinction coefficient on three contrasting lakes in the English Lake
871 District. *Freshw. Biol.* 53, 2573–2586. <https://doi.org/10.1111/j.1365-2427.2008.02083.x>

872 Bhagowati, B., Ahamad, K.U., 2018. A review on lake eutrophication dynamics and recent developments in
873 lake modeling. *Ecohydrol. Hydrobiol.* <https://doi.org/10.1016/j.ecohyd.2018.03.002>

- 874 Bonnet, M., Poulin, M., 2004. DyLEM-1D: a 1D physical and biochemical model for planktonic succession,
875 nutrients and dissolved oxygen cycling application to a hyper-eutrophic reservoir. *Ecol. Model.* 180,
876 317–344. <https://doi.org/10.1016/j.ecolmodel.2004.04.037>
- 877 Brentrup, J.A., Williamson, C.E., Colom-Montero, W., Eckert, W., de Eyto, E., Grossart, H.-P., Huot, Y.,
878 Isles, P.D.F., Knoll, L.B., Leach, T.H., McBride, C.G., Pierson, D., Pomati, F., Read, J.S., Rose,
879 K.C., Samal, N.R., Staehr, P.A., Winslow, L.A., 2016. The potential of high-frequency profiling to
880 assess vertical and seasonal patterns of phytoplankton dynamics in lakes: an extension of the Plank-
881 ton Ecology Group (PEG) model. *INLAND WATERS* 6, 565–580. [https://doi.org/10.5268/IW-](https://doi.org/10.5268/IW-6.4.890)
882 6.4.890
- 883 Brett, M.T., Ahopelto, S.K., Brown, H.K., Brynstad, B.E., Butcher, T.W., Coba, E.E., Curtis, C.A., Dara,
884 J.T., Doeden, K.B., Evans, K.R., Fan, L., Finley, J.D., Garguilo, N.J., Gebreeyesus, S.M., Goodman,
885 M.K., Gray, K.W., Grinnell, C., Gross, K.L., Hite, B.R.E., Jones, A.J., Kenyon, P.T., Klock, A.M.,
886 Koshy, R.E., Lawler, A.M., Lu, M., Martinkosky, L., Miller-Schulze, J.R., Nguyen, Q.T.N., Runde,
887 E.R., Stultz, J.M., Wang, S., White, F.P., Wilson, C.H., Wong, A.S., Wu, S.Y., Wurden, P.G.,
888 Young, T.R., Arhonditsis, G.B., 2016. The modeled and observed response of Lake Spokane
889 hypolimnetic dissolved oxygen concentrations to phosphorus inputs. *LAKE Reserv. Manag.* 32,
890 246–258. <https://doi.org/10.1080/10402381.2016.1170079>
- 891 Brito, D., Neves, R., Branco, M.A., Goncalves, M.C., Ramos, T.B., 2017. Modeling flood dynamics in a
892 temporary river draining to an eutrophic reservoir in southeast Portugal. *Environ. EARTH Sci.* 76.
893 <https://doi.org/10.1007/s12665-017-6713-7>
- 894 Brown, C., Hoyer, M., Bachmann, R., Canfield, D., 2000. Nutrient-chlorophyll relationships: an evaluation
895 of empirical nutrient-chlorophyll models using Florida and north-temperate lake data. *Can. J. Fish.*
896 *Aquat. Sci.* 57, 1574–1583. <https://doi.org/10.1139/f00-090>
- 897 Bruce, L.C., Frassl, M.A., Arhonditsis, G.B., Gal, G., Hamilton, D.P., Hanson, P.C., Hetherington, A.L.,
898 Melack, J.M., Read, J.S., Rinke, K., Rigosi, A., Trolle, D., Winslow, L., Adrian, R., Ayala, A.I.,
899 Bocaniov, S.A., Boehrer, B., Boon, C., Brookes, J.D., Bueche, T., Busch, B.D., Copetti, D., Cortés,
900 A., de Eyto, E., Elliott, J.A., Gallina, N., Gilboa, Y., Guyennon, N., Huang, L., Kerimoglu, O.,

901 Lenters, J.D., MacIntyre, S., Makler-Pick, V., McBride, C.G., Moreira, S., Özkundakci, D., Pilotti,
902 M., Rueda, F.J., Rusak, J.A., Samal, N.R., Schmid, M., Shatwell, T., Snorthheim, C., Soullignac, F.,
903 Valerio, G., van der Linden, L., Vetter, M., Vinçon-Leite, B., Wang, J., Weber, M., Wickramaratne,
904 C., Woolway, R.I., Yao, H., Hipsey, M.R., 2018. A multi-lake comparative analysis of the General
905 Lake Model (GLM): Stress-testing across a global observatory network. *Environ. Model. Softw.*
906 102, 274–291. <https://doi.org/10.1016/j.envsoft.2017.11.016>

907 Bruce, L.C., Hamilton, D., Imberger, J., Gal, G., Gophen, M., Zohary, T., Hambright, K.D., 2006. A numeri-
908 cal simulation of the role of zooplankton in C, N and P cycling in Lake Kinneret, Israel. *Ecol. Mod-*
909 *el.* 193, 412–436. <https://doi.org/10.1016/j.ecolmodel.2005.09.008>

910 Bruggeman, J., Bolding, K., 2014. A general framework for aquatic biogeochemical models. *Environ. Mod-*
911 *el. Softw.* 61, 249–265.

912 Burger, D.F., Hamilton, D.P., Pilditch, C.A., 2008. Modelling the relative importance of internal and external
913 nutrient loads on water column nutrient concentrations and phytoplankton biomass in a shallow
914 polymictic lake. *Ecol. Model.* 211, 411–423. <https://doi.org/10.1016/j.ecolmodel.2007.09.028>

915 Carey, C.C., Ibelings, B.W., Hoffmann, E.P., Hamilton, D.P., Brookes, J.D., 2012. Eco-physiological adapta-
916 tions that favour freshwater cyanobacteria in a changing climate. *Water Res.* 46, 1394–1407.
917 <https://doi.org/10.1016/j.watres.2011.12.016>

918 Carraro, E., Guyennon, N., Hamilton, D., Valsecchi, L., Manfredi, E.C., Viviano, G., Salerno, F., Tartari, G.,
919 Copetti, D., 2012. Coupling high-resolution measurements to a three-dimensional lake model to as-
920 sess the spatial and temporal dynamics of the cyanobacterium *Planktothrix rubescens* in a medium-
921 sized lake. *Hydrobiologia* 698, 77–95. <https://doi.org/10.1007/s10750-012-1096-y>

922 Carvalho, L., Miller nee (Ferguson), C.A., Scott, E.M., Codd, G.A., Davies, P.S., Tyler, A.N., 2011.
923 Cyanobacterial blooms: Statistical models describing risk factors for national-scale lake assessment
924 and lake management. *Sci. TOTAL Environ.* 409, 5353–5358.
925 <https://doi.org/10.1016/j.scitotenv.2011.09.030>

- 926 Cha, Y., Park, S.S., Kim, K., Byeon, M., Stow, C.A., 2014. Probabilistic prediction of cyanobacteria abun-
927 dance in a Korean reservoir using a Bayesian Poisson model. *WATER Resour. Res.* 50, 2518–2532.
928 <https://doi.org/10.1002/2013WR014372>
- 929 Chanudet, V., Fabre, V., van der Kaaij, T., 2012. Application of a three-dimensional hydrodynamic model to
930 the Nam Theun 2 Reservoir (Lao PDR). *J. Gt. Lakes Res.* 38, 260–269.
931 <https://doi.org/10.1016/j.jglr.2012.01.008>
- 932 Chapra, S.C., Canale, R.P., 1991. Long-term phenomenological model of phosphorus and oxygen for strati-
933 fied lakes. *Water Res.* 25, 707–715. [https://doi.org/10.1016/0043-1354\(91\)90046-S](https://doi.org/10.1016/0043-1354(91)90046-S)
- 934 Chaves, P., Kojiri, T., 2007. Conceptual fuzzy neural network model for water quality simulation. *Hydrol.*
935 *Process.* 21, 634–646. <https://doi.org/10.1002/hyp.6279>
- 936 Chen, W.-B., Liu, W.-C., 2014. Artificial neural network modeling of dissolved oxygen in reservoir. *Envi-*
937 *ron. Monit. Assess.* 186, 1203–1217. <https://doi.org/10.1007/s10661-013-3450-6>
- 938 Chung, E.G., Bombardelli, F.A., Schladow, S.G., 2009. Modeling linkages between sediment resuspension
939 and water quality in a shallow, eutrophic, wind-exposed lake. *Ecol. Model.* 220, 1251–1265.
940 <https://doi.org/10.1016/j.ecolmodel.2009.01.038>
- 941 Crave, A., Lacroix G., Durand P., Vinçon-Leite B., Ménesguen A., Sánchez-Pérez J.-M., Sauvage S., Sau-
942 vage, S., 2017. Modélisation de l'eutrophisation, in: *L'eutrophisation: Manifestations, Causes,*
943 *Conséquences et Prédicibilité. Rapport d'Expertise Scientifique Collective.* pp. 648–789.
- 944 Crisci, C., Terra, R., Pacheco, J.P., Ghattas, B., Bidegain, M., Goyenola, G., Lagomarsino, J.J., Méndez, G.,
945 Mazzeo, N., 2017. Multi-model approach to predict phytoplankton biomass and composition dynam-
946 ics in a eutrophic shallow lake governed by extreme meteorological events. *Ecol. Model.* 360, 80–
947 93. <https://doi.org/10.1016/j.ecolmodel.2017.06.017>
- 948 Cui, Y., Zhu, G., Li, H., Luo, L., Cheng, X., Jin, Y., Trolle, D., 2016. Modeling the response of phytoplank-
949 ton to reduced external nutrient load in a subtropical Chinese reservoir using DYRESM-CAEDYM.
950 *LAKE Reserv. Manag.* 32, 146–157. <https://doi.org/10.1080/10402381.2015.1136365>

951 Curtarelli, M.P., Ogashawara, I., Alcântara, E.H., Stech, J.L., 2015. Coupling remote sensing bio-optical and
952 three-dimensional hydrodynamic modeling to study the phytoplankton dynamics in a tropical hydro-
953 electric reservoir. *Remote Sens. Environ.* 157, 185–198. <https://doi.org/10.1016/j.rse.2014.06.013>

954 Dash, P., Walker, N.D., Mishra, D.R., Hu, C., Pinckney, J.L., D'Sa, E.J., 2011. Estimation of cyanobacterial
955 pigments in a freshwater lake using OCM satellite data. *Remote Sens. Environ.* 115, 3409–3423.
956 <https://doi.org/10.1016/j.rse.2011.08.004>

957 De Senerpont Domis, L.N., Van de Waal, D.B., Helmsing, N.R., Van Donk, E., Mooij, W.M., 2014. Com-
958 munity stoichiometry in a changing world: combined effects of warming and eutrophication on phy-
959 toplankton dynamics. *Ecology* 95, 1485–1495. <https://doi.org/10.1890/13-1251.1>

960 DeAngelis, D.L., Mooij, W.M., 2005. Individual-based modeling of ecological and evolutionary processes.
961 *Annu. Rev. Ecol. Evol. Syst.* 36, 147–168.
962 <https://doi.org/10.1146/annurev.ecolsys.36.102003.152644>

963 Deus, R., Brito, D., Kenov, I.A., Lima, M., Costa, V., Medeiros, A., Neves, R., Alves, C.N., 2013. Three-
964 dimensional model for analysis of spatial and temporal patterns of phytoplankton in Tucuruí reser-
965 voir, Pará, Brazil. *Ecol. Model.* 253, 28–43. <https://doi.org/10.1016/j.ecolmodel.2012.10.013>

966 Diaz Muniz, C., Alonso Fernandez, J.R., Garcia Nieto, P.J., Alvarez Anton, J.C., 2015. Modelling algal ab-
967 normal proliferation in a reservoir using support vector regression: a case study.
968 *ECOHYDROLOGY* 8, 1109–1118. <https://doi.org/10.1002/eco.1568>

969 Dillon, P.J., Rigler, F.H., 1974a. The phosphorus-chlorophyll relationship in lakes1,2: Phosphorus-
970 chlorophyll relationship. *Limnol. Oceanogr.* 19, 767–773. <https://doi.org/10.4319/lo.1974.19.5.0767>

971 Dillon, P.J., Rigler, F.H., 1974b. A Test of a Simple Nutrient Budget Model Predicting the Phosphorus Con-
972 centration in Lake Water. *J. Fish. Res. Board Can.* 31, 1771–1778. <https://doi.org/10.1139/f74-225>

973 Ditoro, D., Thomas, N., Herdendorf, C., Winfield, R., Connolly, J.P., 1987. A post audit of a lake Erie eu-
974 trophication model. *J. Gt. Lakes Res.* 13, 801–825. [https://doi.org/10.1016/S0380-1330\(87\)71692-X](https://doi.org/10.1016/S0380-1330(87)71692-X)

975 Dodds, W.K., 2006. Eutrophication and trophic state in rivers and streams. *Limnol. Oceanogr.* 51, 671–680.
976 https://doi.org/10.4319/lo.2006.51.1_part_2.0671

977 Droop, M.R., 1968. Vitamin B12 and Marine Ecology. IV. The Kinetics of Uptake, Growth and Inhibition in
978 *Monochrysis Lutheri*. *J. Mar. Biol. Assoc. U. K.* 48, 689.
979 <https://doi.org/10.1017/S0025315400019238>

980 Easthope, M.P., Howard, A., 1999. Simulating cyanobacterial growth in a lowland reservoir. *Sci. Total Envi-*
981 *ron.* 241, 17–25. [https://doi.org/10.1016/S0048-9697\(99\)00278-8](https://doi.org/10.1016/S0048-9697(99)00278-8)

982 Elliott, 2011. Predicting the impact of changing nutrient load and temperature on the phytoplankton of Eng-
983 land’s largest lake, Windermere. *Freshw. Biol.* 1365–2427.

984 Elliott, A., Turek, G., Snow, V., Rutledge, D., Ritchie, A., Herzig, A., 2014. Testing Tales: Selection and
985 Evaluation of a Framework for Interoperable Freshwater Modelling, in: *Proceedings of the 7th Inter-*
986 *national Congress on Environmental Modelling and Software.* Presented at the 7th International
987 Congress on Environmental Modelling and Software, International Environmental Modelling and
988 Software Society (iEMSs), San Diego, California, USA., p. 9.

989 Elliott, J., Thackeray, S., 2004. The simulation of phytoplankton in shallow and deep lakes using PROTECH.
990 *Ecol. Model.* 178, 357–369. <https://doi.org/10.1016/j.ecolmodel.2004.02.012>

991 Elliott, J., Thackeray, S., Huntingford, C., Jones, R., 2005. Combining a regional climate model with a phy-
992 toplankton community model to predict future changes in phytoplankton in lakes. *Freshw. Biol.* 50,
993 1404–1411. <https://doi.org/10.1111/j.1365-2427.2005.01409.x>

994 Elliott, J.A., 2012. Is the future blue-green? A review of the current model predictions of how climate change
995 could affect pelagic freshwater cyanobacteria. *Water Res.* 46, 1364–1371.
996 <https://doi.org/10.1016/j.watres.2011.12.018>

997 Elliott, J.A., Defew, L., 2012. Modelling the response of phytoplankton in a shallow lake (Loch Leven, UK)
998 to changes in lake retention time and water temperature. *HYDROBIOLOGIA* 681, 105–116.
999 <https://doi.org/10.1007/s10750-011-0930-y>

1000 Elliott, J.A., Persson, I., Thackeray, S.J., Blenckner, T., 2007. Phytoplankton modelling of Lake Erken, Swe-
1001 den by linking the models PROBE and PROTECH. *Ecol. Model.* 202, 421–426.
1002 <https://doi.org/10.1016/j.ecolmodel.2006.11.004>

1003 Elliott, Jones, I.D., Page, T., 2009. The importance of nutrient source in determining the influence of reten-
1004 tion time on phytoplankton: an explorative modelling study of a naturally well-flushed lake.
1005 *Hydrobiologia* 627, 129–142. <https://doi.org/10.1007/s10750-009-9720-1>

1006 Elshaarawi, A., 1984. Dissolved-oxygen concentrations in Lake Erie (USA-Canada) .2. A statistical-model
1007 for dissolved-oxygen in the central basin of Lake Erie. *J. Hydrol.* 72, 231–243.
1008 [https://doi.org/10.1016/0022-1694\(84\)90082-9](https://doi.org/10.1016/0022-1694(84)90082-9)

1009 Elshorbagy, A., Ormsbee, L., 2006. Object-oriented modeling approach to surface water quality manage-
1010 ment. *Environ. Model. Softw.* 21, 689–698. <https://doi.org/10.1016/j.envsoft.2005.02.001>

1011 European Environment Agency, 2012. Climate change, impacts and vulnerability in Europe 2012 (Publica-
1012 tion).

1013 Everett, J.D., Baird, M.E., Suthers, I.M., 2007. Nutrient and plankton dynamics in an intermittently
1014 closed/open lagoon, Smiths Lake, south-eastern Australia: An ecological model. *Estuar. Coast. Shelf*
1015 *Sci.* 72, 690–702. <https://doi.org/10.1016/j.ecss.2006.12.001>

1016 Fadel, A., Lemaire, B.J., Vincon-Leite, B., Atoui, A., Slim, K., Tassin, B., 2017. On the successful use of a
1017 simplified model to simulate the succession of toxic cyanobacteria in a hypereutrophic reservoir with
1018 a highly fluctuating water level. *Environ. Sci. Pollut. Res.* 24, 20934–20948.
1019 <https://doi.org/10.1007/s11356-017-9723-9>

1020 Fang, X., Stefan, H., 1997. Simulated climate change effects on dissolved oxygen characteristics in ice-
1021 covered lakes. *Ecol. Model.* 103, 209–229. [https://doi.org/10.1016/S0304-3800\(97\)00086-0](https://doi.org/10.1016/S0304-3800(97)00086-0)

1022 Fang, X., Stefan, H.G., 2009. Simulations of climate effects on water temperature, dissolved oxygen, and ice
1023 and snow covers in lakes of the contiguous United States under past and future climate scenarios.
1024 *Limnol. Oceanogr.* 54, 2359–2370. https://doi.org/10.4319/lo.2009.54.6_part_2.2359

1025 Fennel, K., Collier, R., Larson, G., Crawford, G., Boss, E., 2007. Seasonal nutrient and plankton dynamics in
1026 a physical-biological model of Crater Lake. *Hydrobiologia* 574, 265–280.
1027 <https://doi.org/10.1007/s10750-006-2615-5>

- 1028 Fernandez, J.A., Clavero, V., Villalobos, J.A., Niell, F.X., 1997. A non-linear model of phosphorus flux in
1029 the phytoplankton of a temperate eutrophic reservoir. *Hydrobiologia* 344, 205–214.
1030 <https://doi.org/10.1023/A:1002910529075>
- 1031 Fiksen, Ø., Follows, M.J., Aksnes, D.L., 2013. Trait-based models of nutrient uptake in microbes extend the
1032 Michaelis-Menten framework. *Limnol. Oceanogr.* 58, 193–202.
1033 <https://doi.org/10.4319/lo.2013.58.1.0193>
- 1034 Flynn, K.J., 2010. Ecological modelling in a sea of variable stoichiometry: Dysfunctionality and the legacy
1035 of Redfield and Monod. *Prog. Oceanogr.* 84, 52–65. <https://doi.org/10.1016/j.pocean.2009.09.006>
- 1036 Flynn, K.J., 2005. Castles built on sand: dysfunctionality in plankton models and the inadequacy of dialogue
1037 between biologists and modellers. *J. Plankton Res.* 27, 1205–1210.
1038 <https://doi.org/10.1093/plankt/fbi099>
- 1039 Fornarelli, R., Galelli, S., Castelletti, A., Antenucci, J.P., Marti, C.L., 2013. An empirical modeling approach
1040 to predict and understand phytoplankton dynamics in a reservoir affected by interbasin water trans-
1041 fers. *WATER Resour. Res.* 49, 3626–3641. <https://doi.org/10.1002/wrcr.20268>
- 1042 Fragoso, C.R., Motta Marques, D.M.L., Collischonn, W., Tucci, C.E.M., van Nes, E.H., 2008. Modelling
1043 spatial heterogeneity of phytoplankton in Lake Mangueira, a large shallow subtropical lake in South
1044 Brazil. *Ecol. Model.* 219, 125–137. <https://doi.org/10.1016/j.ecolmodel.2008.08.004>
- 1045 Frisk, T., 1982. An oxygen model for Lake Haukivesi. *Hydrobiologia* 86, 7.
1046 <https://doi.org/10.1007/BF00005800>
- 1047 Frisk, T., Bilaletdin, A., Kaipainen, H., Malve, O., Mols, M., 1999. Modelling phytoplankton dynamics of
1048 the eutrophic Lake Vortsjarv, Estonia. *Hydrobiologia* 414, 59–69.
1049 <https://doi.org/10.1023/A:1003802912687>
- 1050 Gal, G., Hipsey, M.R., Parparov, A., Wagner, U., Makler, V., Zohary, T., 2009. Implementation of ecologi-
1051 cal modeling as an effective management and investigation tool: Lake Kinneret as a case study. *Ecol.*
1052 *Model.* 220, 1697–1718. <https://doi.org/10.1016/j.ecolmodel.2009.04.010>

- 1053 Gal, G., Makler-Pick, V., Shachar, N., 2014. Dealing with uncertainty in ecosystem model scenarios: Appli-
1054 cation of the single-model ensemble approach. *Environ. Model. Softw.* 61, 360–370.
1055 <https://doi.org/10.1016/j.envsoft.2014.05.015>
- 1056 Garcia-Nieto, P.J., Garcia-Gonzalo, E., Alonso Fernandez, J.R., Diaz Muniz, C., 2018. Predictive modelling
1057 of eutrophication in the Pozn de la Dolores lake (Northern Spain) by using an evolutionary support
1058 vector machines approach. *J. Math. Biol.* 76, 817–840. <https://doi.org/10.1007/s00285-017-1161-2>
- 1059 Giguet-Covex, C., Arnaud, F., Poulenard, J., Enters, D., Reyss, J.-L., Millet, L., Lazzaroto, J., Vidal, O.,
1060 2010. Sedimentological and geochemical records of past trophic state and hypolimnetic anoxia in
1061 large, hard-water Lake Bourget, French Alps. *J. Paleolimnol.* 43, 171–190.
- 1062 Gkelis, S., Zaoutsos, N., 2014. Cyanotoxin occurrence and potentially toxin producing cyanobacteria in
1063 freshwaters of Greece: A multi-disciplinary approach. *Toxicon* 78, 1–9.
1064 <https://doi.org/10.1016/j.toxicon.2013.11.010>
- 1065 Gudimov, A., McCulloch, J., Chen, J., Doan, P., Arhonditsis, G., Dittrich, M., 2016. Modeling the interplay
1066 between deepwater oxygen dynamics and sediment diagenesis in a hard-water mesotrophic lake.
1067 *Ecol. Inform.* 31, 59–69. <https://doi.org/10.1016/j.ecoinf.2015.11.005>
- 1068 Gulliver, J., Stephan, H., 1982. Lake phytoplankton model with destratification. *J. Environ. Eng. Div.-Asce*
1069 108, 864–882.
- 1070 Guven, B., Howard, A., 2006. A review and classification of the existing models of cyanobacteria. *Prog.*
1071 *Phys. Geogr.* 30, 1–24. <https://doi.org/10.1191/0309133306pp464ra>
- 1072 Haith, D.A., Hollingshead, N., Bell, M.L., Kreszewski, S.W., Morey, S.J., 2012. Nutrient Loads to Cayuga
1073 Lake, New York: Watershed Modeling on a Budget. *J. WATER Resour. Plan. Manag.-ASCE* 138,
1074 571–580. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000198](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000198)
- 1075 Håkanson, L., 1995. Optimal size of predictive models. *Ecol. Model.* 78, 195–204.
1076 [https://doi.org/10.1016/0304-3800\(93\)E0103-A](https://doi.org/10.1016/0304-3800(93)E0103-A)
- 1077 Hallstan, S., Johnson, R.K., Willén, E., Grandin, U., 2012. Comparison of classification-then-modelling and
1078 species-by-species modelling for predicting lake phytoplankton assemblages. *Ecol. Model.* 231, 11–
1079 19. <https://doi.org/10.1016/j.ecolmodel.2012.01.018>

- 1080 Hamblin, P.F., Bootsma, H.A., Hecky, R.E., 2003. Modeling Nutrient Upwelling in Lake Malawi/Nyasa. *J.*
1081 *Gt. Lakes Res.* 29, 34–47. [https://doi.org/10.1016/S0380-1330\(03\)70537-1](https://doi.org/10.1016/S0380-1330(03)70537-1)
- 1082 Hamilton, D.P., Schladow, S.G., 1997. Prediction of water quality in lakes and reservoirs. Part I — Model
1083 description. *Ecol. Model.* 96, 91–110. [https://doi.org/10.1016/S0304-3800\(96\)00062-2](https://doi.org/10.1016/S0304-3800(96)00062-2)
- 1084 Hamilton, G., McVinish, R., Mengersen, K., 2009. Bayesian model averaging for harmful algal bloom pre-
1085 diction. *Ecol. Appl.* 19, 1805–1814. <https://doi.org/10.1890/08-1843.1>
- 1086 Harada, M., Douma, A., Hiramatsu, K., Nguyen, D.T., Marui, A., 2013. Analysis of seasonal changes in
1087 water qualities in eutrophic reservoirs in a flat low-lying agricultural area using an algae-based eco-
1088 system model: water quality analysis using an algae-based ecosystem model. *Irrig. Drain.* 62, 24–35.
1089 <https://doi.org/10.1002/ird.1770>
- 1090 Hassan, H., Hanaki, K., Matsuo, T., 1998. A modeling approach to simulate impact of climate change in lake
1091 water quality: Phytoplankton growth rate assessment. *WATER Sci. Technol.* 37, 177–185.
1092 [https://doi.org/10.1016/S0273-1223\(98\)00022-5](https://doi.org/10.1016/S0273-1223(98)00022-5)
- 1093 Hellweger, F.L., 2017. 75 years since Monod: It is time to increase the complexity of our predictive ecosys-
1094 tem models (opinion). *Ecol. Model.* 346, 77–87. <https://doi.org/10.1016/j.ecolmodel.2016.12.001>
- 1095 Hellweger, F.L., Kravchuk, E.S., Novotny, V., Gladyshev, M.I., 2008. Agent-based modeling of the complex
1096 life cycle of a cyanobacterium (*Anabaena*) in a shallow reservoir. *Limnol. Oceanogr.* 53, 1227–1241.
1097 <https://doi.org/10.4319/lo.2008.53.4.1227>
- 1098 Hense, I., 2010. Approaches to model the life cycle of harmful algae. *J. Mar. Syst.* 83, 108–114.
1099 <https://doi.org/10.1016/j.jmarsys.2010.02.014>
- 1100 Hense, I., Beckmann, A., 2010. The representation of cyanobacteria life cycle processes in aquatic ecosystem
1101 models. *Ecol. Model.* 221, 2330–2338. <https://doi.org/10.1016/j.ecolmodel.2010.06.014>
- 1102 Hense, I., Beckmann, A., 2006. Towards a model of cyanobacteria life cycle—effects of growing and resting
1103 stages on bloom formation of N₂-fixing species. *Ecol. Model.* 195, 205–218.
1104 <https://doi.org/10.1016/j.ecolmodel.2005.11.018>

- 1105 Hillmer, I., van Reenen, P., Imberger, J., Zohary, T., 2008. Phytoplankton patchiness and their role in the
1106 modelled productivity of a large, seasonally stratified lake. *Ecol. Model.* 218, 49–59.
1107 <https://doi.org/10.1016/j.ecolmodel.2008.06.017>
- 1108 Hipsey, M., Antenucci, J., Hamilton, D., 2011. Computational aquatic ecosystem dynamics model:
1109 CAEDYM v3.2, Science Manual. Univ. West. Aust.
- 1110 Hollander, D.J., McKenzie, J.A., Hsu, K.J., Huc, A.Y., 1993. Application of an eutrophic lake model to the
1111 origin of ancient organic-carbon-rich sediments. *Glob. Biogeochem. Cycles* 7, 157–179.
1112 <https://doi.org/10.1029/92GB02831>
- 1113 Hongping, P., Yong, W., 2003. Eutrophication research of West Lake, Hangzhou, China: modeling under
1114 uncertainty. *Water Res.* 37, 416–428. [https://doi.org/10.1016/s0043-1354\(02\)00287-7](https://doi.org/10.1016/s0043-1354(02)00287-7)
- 1115 Hou, G., Song, L., Liu, J., Xiao, B., Liu, Y., 2004. Modeling of cyanobacterial blooms in hypereutrophic
1116 Lake Dianchi, China. *J. Freshw. Ecol.* 19, 623–629. <https://doi.org/10.1080/02705060.2004.9664743>
- 1117 Howard, A., Easthope, M., 2002. Application of a model to predict cyanobacterial growth patterns in re-
1118 sponse to climatic change at Farmoor Reservoir, Oxfordshire, UK. *Sci. TOTAL Environ.* 282, 459–
1119 469. [https://doi.org/10.1016/S0048-9697\(01\)00929-9](https://doi.org/10.1016/S0048-9697(01)00929-9)
- 1120 Howard, A., Irish, A.E., Reynolds, C.S., 1996. A new simulation of cyanobacterial underwater movement
1121 (SCUM'96). *J. Plankton Res.* 18, 1375–1385. <https://doi.org/10.1093/plankt/18.8.1375>
- 1122 Huang, J., Gao, J., Hoermann, G., 2012. Hydrodynamic-phytoplankton model for short-term forecasts of
1123 phytoplankton in Lake Taihu, China. *Limnologica* 42, 7–18.
1124 <https://doi.org/10.1016/j.limno.2011.06.003>
- 1125 Huang, J., Gao, J., Hoermann, G., Fohrer, N., 2014. Modeling the effects of environmental variables on
1126 short-term spatial changes in phytoplankton biomass in a large shallow lake, Lake Taihu. *Environ.*
1127 *Earth Sci.* 72, 3609–3621. <https://doi.org/10.1007/s12665-014-3272-z>
- 1128 Huang, J., Gao, J., Liu, J., Zhang, Y., 2013. State and parameter update of a hydrodynamic-phytoplankton
1129 model using ensemble Kalman filter. *Ecol. Model.* 263, 81–91.
1130 <https://doi.org/10.1016/j.ecolmodel.2013.04.022>

- 1131 Huang, J., Xu, Q., Wang, X., Xi, B., Jia, K., Huo, S., Liu, H., Li, C., Xu, B., 2015. Evaluation of a Modified
1132 Monod Model for Predicting Algal Dynamics in Lake Tai. *Water* 7, 3626–3642.
1133 <https://doi.org/10.3390/w7073626>
- 1134 Huang, Z., Xue, B., Pang, Y., 2009. Simulation on stream flow and nutrient loadings in Gucheng Lake, Low
1135 Yangtze River Basin, based on SWAT model. *Quat. Int.* 208, 109–115.
1136 <https://doi.org/10.1016/j.quaint.2008.12.018>
- 1137 Huszar, V.L.M., Caraco, N.F., Roland, F., Cole, J., 2006. Nutrient-chlorophyll relationships in tropical sub-
1138 tropical lakes: do temperate models fit? *Biogeochemistry* 79, 239–250.
1139 <https://doi.org/10.1007/s10533-006-9007-9>
- 1140 Jeong, I.I., Lou, I., Ung, W.K., Mok, K.M., 2015. Using Principle Component Regression, Artificial Neural
1141 Network, and Hybrid Models for Predicting Phytoplankton Abundance in Macau Storage Reservoir.
1142 *Environ. Model. Assess.* 20, 355–365. <https://doi.org/10.1007/s10666-014-9433-3>
- 1143 Imboden, D.M., 1974. Phosphorus model of lake eutrophication: P model of lake eutrophication. *Limnol.*
1144 *Oceanogr.* 19, 297–304. <https://doi.org/10.4319/lo.1974.19.2.0297>
- 1145 Imboden, D.M., Gächter, R., 1978. A dynamic lake model for trophic state prediction. *Ecol. Model.* 4, 77–
1146 98. [https://doi.org/10.1016/0304-3800\(78\)90001-7](https://doi.org/10.1016/0304-3800(78)90001-7)
- 1147 Inkala, A., Hellsten, S., Heikkinen, M., 1998. Integrated 3D modelling of water circulation and the dynamics
1148 of phytoplankton; the effects of a planned reservoir. *Int. Rev. Hydrobiol.* 83, 681–688.
- 1149 Janse, J.H., Scheffer, M., Lijklema, L., Van Liere, L., Sloot, J.S., Mooij, W.M., 2010. Estimating the critical
1150 phosphorus loading of shallow lakes with the ecosystem model PCLake: Sensitivity, calibration and
1151 uncertainty. *Ecol. Model.* 221, 654–665. <https://doi.org/10.1016/j.ecolmodel.2009.07.023>
- 1152 Jayaweera, M., Asaeda, T., 1996. Modeling of biomanipulation in shallow, eutrophic lakes: An application
1153 to Lake Bleiswijkse Zoom, the Netherlands. *Ecol. Model.* 85, 113–127.
1154 [https://doi.org/10.1016/0304-3800\(94\)00153-7](https://doi.org/10.1016/0304-3800(94)00153-7)
- 1155 Jenny, J.P., Arnaud, F., Dorioz, J.M., Covex, C.G., Frossard, V., Sabatier, P., Millet, L., Reyss, J.L.,
1156 Tachikawa, K., Bard, E., Pignol, C., Soufi, F., Romeyer, O., Perga, M.E., 2013. A spatiotemporal in-
1157 vestigation of varved sediments highlights the dynamics of hypolimnetic hypoxia in a large hard-

1158 water lake over the last 150 years. *Limnol. Oceanogr.* 58, 1395–1408.
1159 <https://doi.org/10.4319/lo.2013.58.4.1395>

1160 Ji, D., Xi, B., Su, J., Huo, S., Wang, J., Gong, F., Li, M., Jia, X., Wei, D., 2014. Structure equation model-
1161 based approach for determining lake nutrient standards in Yungui Plateau ecoregion and Eastern
1162 Plain ecoregion lakes, China. *Environ. EARTH Sci.* 72, 3067–3077. [https://doi.org/10.1007/s12665-](https://doi.org/10.1007/s12665-014-3212-y)
1163 [014-3212-y](https://doi.org/10.1007/s12665-014-3212-y)

1164 Jones, I.D., Elliott, J.A., 2007. Modelling the effects of changing retention time on abundance and composi-
1165 tion of phytoplankton species in a small lake. *Freshw. Biol.* 52, 988–997.
1166 <https://doi.org/10.1111/j.1365-2427.2007.01746.x>

1167 Jones, J.R., Bachmann, R.W., 1976. Prediction of Phosphorus and Chlorophyll Levels in Lakes. *J. Water*
1168 *Pollut. Control Fed.* 48, 2176–2182.

1169 Jørgensen, S.E., 2015. Structurally dynamic models: a new promising model type. *Environ. Earth Sci.* 74,
1170 7041–7048. <https://doi.org/10.1007/s12665-015-4735-6>

1171 Jørgensen, S.E., 2010. A review of recent developments in lake modelling. *Ecol. Model.* 221, 689–692.
1172 <https://doi.org/10.1016/j.ecolmodel.2009.10.022>

1173 Jørgensen, S.E., 1990. Ecosystem theory, ecological buffer capacity, uncertainty and complexity. *Ecol. Mod-*
1174 *el.* 52, 125–133. [https://doi.org/10.1016/0304-3800\(90\)90013-7](https://doi.org/10.1016/0304-3800(90)90013-7)

1175 Jørgensen, S.E., Fath, B.D., 2001. *Fundamentals of ecological modelling.* Elsevier.

1176 Jung, N.-C., Popescu, I., Kelderman, P., Solomatine, D.P., Price, R.K., 2010. Application of model trees and
1177 other machine learning techniques for algal growth prediction in Yongdam reservoir, Republic of
1178 Korea. *J. Hydroinformatics* 12, 262–274. <https://doi.org/10.2166/hydro.2009.004>

1179 Kerimoglu, O., Hofmeister, R., Maerz, J., Riethmüller, R., Wirtz, K.W., 2017. The acclimative biogeochem-
1180 ical model of the southern North Sea. *Biogeosciences* 14, 4499–4531. [https://doi.org/10.5194/bg-14-](https://doi.org/10.5194/bg-14-4499-2017)
1181 [4499-2017](https://doi.org/10.5194/bg-14-4499-2017)

1182 Kim, D.K., Jeong, K.S., McKay, R.I.B., Chon, T.S., Joo, G.J., 2012. Machine Learning for Predictive Man-
1183 agement: Short and Long term Prediction of Phytoplankton Biomass using Genetic Algorithm Based
1184 Recurrent Neural Networks. *Int. J. Environ. Res.* 6, 95–108. <https://doi.org/10.22059/ijer.2011.476>

- 1185 Kromkamp, J., Walsby, A.E., 1990. A computer model of buoyancy and vertical migration in cyanobacteria.
1186 J. Plankton Res. 12, 161–183. <https://doi.org/10.1093/plankt/12.1.161>
- 1187 Kuo, J., Thomann, R., 1983. Phytoplankton modeling in the embayments of lakes. J. Environ. Eng.-Asce
1188 109, 1311–1332.
- 1189 Kutas, T., Toth, J., 1985. A stochastic-model of phytoplankton dynamics in Lake Balaton. J. Stat. Comput.
1190 Simul. 21, 241–264. <https://doi.org/10.1080/00949658508810818>
- 1191 Le Moal, M., Gascuel-Oudou, C., Ménesguen, A., Souchon, Y., Étrillard, C., Levain, A., Moatar, F., Pan-
1192 nard, A., Souchu, P., Lefebvre, A., Pinay, G., 2018. Eutrophication: A new wine in an old bottle?
1193 Sci. Total Environ. <https://doi.org/10.1016/j.scitotenv.2018.09.139>
- 1194 Leon, L.F., Smith, R.E.H., Hipsey, M.R., Bocaniov, S.A., Higgins, S.N., Hecky, R.E., Antenucci, J.P.,
1195 Imberger, J.A., Guildford, S.J., 2011. Application of a 3D hydrodynamic-biological model for sea-
1196 sonal and spatial dynamics of water quality and phytoplankton in Lake Erie. J. Gt. Lakes Res. 37,
1197 41–53. <https://doi.org/10.1016/j.jglr.2010.12.007>
- 1198 Leon, L.F., Smith, R.E.H., Malkin, S.Y., Depew, D., Hipsey, M.R., Antenucci, J.P., Higgins, S.N., Hecky,
1199 R.E., Rao, R.Y., 2012. Nested 3D modeling of the spatial dynamics of nutrients and phytoplankton
1200 in a Lake Ontario nearshore zone. J. Gt. Lakes Res. 38, 171–183.
1201 <https://doi.org/10.1016/j.jglr.2012.02.006>
- 1202 Lewis, D.M., Elliott, J.A., Lambert, M.F., Reynolds, C.S., 2002. The simulation of an Australian reservoir
1203 using a phytoplankton community model: protech. Ecol. Model. 150, 107–116.
1204 [https://doi.org/10.1016/S0304-3800\(01\)00466-5](https://doi.org/10.1016/S0304-3800(01)00466-5)
- 1205 Li, W., Qin, B., Zhu, G., 2014. Forecasting short-term cyanobacterial blooms in Lake Taihu, China, using a
1206 coupled hydrodynamic–algal biomass model. Ecohydrology 7, 794–802.
1207 <https://doi.org/10.1002/eco.1402>
- 1208 Li, Y., Gal, G., Makler-Pick, V., Waite, A.M., Bruce, L.C., Hipsey, M.R., 2014. Examination of the role of
1209 the microbial loop in regulating lake nutrient stoichiometry and phytoplankton dynamics.
1210 Biogeosciences 11, 2939–2960. <https://doi.org/10.5194/bg-11-2939-2014>

- 1211 Li, Y., Liu, Y., Zhao, L., Hastings, A., Guo, H., 2015. Exploring change of internal nutrients cycling in a
1212 shallow lake: A dynamic nutrient driven phytoplankton model. *Ecol. Model.* 313, 137–148.
1213 <https://doi.org/10.1016/j.ecolmodel.2015.06.025>
- 1214 Lindim, C., Becker, A., Grueneberg, B., Fischer, H., 2015. Modelling the effects of nutrient loads reduction
1215 and testing the N and P control paradigm in a German shallow lake. *Ecol. Eng.* 82, 415–427.
1216 <https://doi.org/10.1016/j.ecoleng.2015.05.009>
- 1217 Liu, B., 2013. Global dynamic behaviors for a delayed Nicholson’s blowflies model with a linear harvesting
1218 term. *Electron. J. Qual. THEORY Differ. Equ.* 1–13.
- 1219 Liu, W.C., Chen, H.H., Hsieh, W.H., Chang, C.H., 2006. Linking watershed and eutrophication modelling
1220 for the Shihmen Reservoir, Taiwan. *Water Sci. Technol.* 54, 39–46.
1221 <https://doi.org/10.2166/wst.2006.834>
- 1222 Liu, Y., Wang, Y., Sheng, H., Dong, F., Zou, R., Zhao, L., Guo, H., Zhu, X., He, B., 2014. Quantitative
1223 evaluation of lake eutrophication responses under alternative water diversion scenarios: A water
1224 quality modeling based statistical analysis approach. *Sci. Total Environ.* 468, 219–227.
1225 <https://doi.org/10.1016/j.scitotenv.2013.08.054>
- 1226 Los, F.H., Brinkman, J.J., 1988. Phytoplankton Modelling by Means of Optimizing: A 10-year Experience
1227 with BLOOM II. *Verhandlungen Int. Ver. Limnol.* 23, 790–795.
- 1228 Los, F.J., 1980. An Algal Bloom Model as a Tool to Simulate Management Measures, in: *Hypertrophic Eco-*
1229 *systems, Developments in Hydrobiology.* Springer, Dordrecht, pp. 171–178.
1230 https://doi.org/10.1007/978-94-009-9203-0_19
- 1231 Lung, W.S., Canale, R.P., Freedman, P.L., 1976. Phosphorus models for eutrophic lakes. *Water Res.* 10,
1232 1101–1114. [https://doi.org/10.1016/0043-1354\(76\)90043-9](https://doi.org/10.1016/0043-1354(76)90043-9)
- 1233 Makler-Pick, V., Gal, G., Hipsey, M.R., 2011. Coupling of an individual-based model with a complex aquat-
1234 ic ecosystem model to explore the impact of the upper trophic level on lower trophic levels, in: *In-*
1235 *ternational Congress on Modelling and Simulation.* Presented at the International Congress on Mod-
1236 elling and Simulation, Perth, Australia, p. 7.

- 1237 Markensten, H., Moore, K., Persson, I., 2010. Simulated lake phytoplankton composition shifts toward cya-
1238 nobacteria dominance in a future warmer climate. *Ecol. Appl.* 20, 752–767.
1239 <https://doi.org/10.1890/08-2109.1>
- 1240 Ménesguen, A., Lacroix, G., 2018. Modelling the marine eutrophication: A review. *Sci. Total Environ.* 636,
1241 339–354. <https://doi.org/10.1016/j.scitotenv.2018.04.183>
- 1242 Mieleitner, J., Reichert, P., 2008. Modelling functional groups of phytoplankton in three lakes of different
1243 trophic state. *Ecol. Model.* 211, 279–291. <https://doi.org/10.1016/j.ecolmodel.2007.09.010>
- 1244 Mieleitner, J., Reichert, P., 2006. Analysis of the transferability of a biogeochemical lake model to lakes of
1245 different trophic state. *Ecol. Model.* 194, 49–61. <https://doi.org/10.1016/j.ecolmodel.2005.10.039>
- 1246 Millie, D.F., Weckman, G.R., Pigg, R.J., Tester, P.A., Dyble, J., Litaker, R.W., Carrick, H.J., Fahnenstiel,
1247 G.L., 2006. Modeling phytoplankton abundance in Saginaw Bay, Lake Huron: Using artificial neural
1248 networks to discern functional influence of environmental variables and relevance to a great lakes
1249 observing system. *J. Phycol.* 42, 336–349. <https://doi.org/10.1111/j.1529-8817.2006.00209.x>
- 1250 Milstead, W.B., Hollister, J.W., Moore, R.B., Walker, H.A., 2013. Estimating Summer Nutrient Concentra-
1251 tions in Northeastern Lakes from SPARROW Load Predictions and Modeled Lake Depth and Vol-
1252 ume. *Plos One* 8, e81457. <https://doi.org/10.1371/journal.pone.0081457>
- 1253 Mooij, W.M., Brederveld, R.J., de Klein, J.J.M., DeAngelis, D.L., Downing, A.S., Faber, M., Gerla, D.J.,
1254 Hipsey, M.R., 't Hoen, J., Janse, J.H., Janssen, A.B.G., Jeuken, M., Kooi, B.W., Lischke, B.,
1255 Petzoldt, T., Postma, L., Schep, S.A., Scholten, H., Teurlincx, S., Thiange, C., Trolle, D., van Dam,
1256 A.A., van Gerven, L.P.A., van Nes, E.H., Kuiper, J.J., 2014. Serving many at once: How a database
1257 approach can create unity in dynamical ecosystem modelling. *Environ. Model. Softw.* 61, 266–273.
1258 <https://doi.org/10.1016/j.envsoft.2014.04.004>
- 1259 Mooij, W.M., Trolle, D., Jeppesen, E., Arhonditsis, G., Belolipetsky, P.V., Chitamwebwa, D.B.R.,
1260 Degermendzhy, A.G., DeAngelis, D.L., De Senerpont Domis, L.N., Downing, A.S., Elliott, J.A.,
1261 Fragoso, C.R., Gaedke, U., Genova, S.N., Gulati, R.D., Håkanson, L., Hamilton, D.P., Hipsey, M.R.,
1262 't Hoen, J., Hülsmann, S., Los, F.H., Makler-Pick, V., Petzoldt, T., Prokopkin, I.G., Rinke, K.,
1263 Schep, S.A., Tominaga, K., Van Dam, A.A., Van Nes, E.H., Wells, S.A., Janse, J.H., 2010. Chal-

- 1264 lenges and opportunities for integrating lake ecosystem modelling approaches. *Aquat. Ecol.* 44, 633–
1265 667. <https://doi.org/10.1007/s10452-010-9339-3>
- 1266 Moore, B.C., Chen, P.-H., Funk, W.H., Yonge, D., 1996. A model for predicting lake sediment oxygen de-
1267 mand following hypolimnetic aeration. *JAWRA J. Am. Water Resour. Assoc.* 32, 723–731.
1268 <https://doi.org/10.1111/j.1752-1688.1996.tb03469.x>
- 1269 Moss, B., 2012. Cogs in the endless machine: Lakes, climate change and nutrient cycles: A review. *Sci. To-
1270 tal Environ., Climate Change and Macronutrient Cycling along the Atmospheric, Terrestrial, Fresh-
1271 water and Estuarine Continuum - A Special Issue dedicated to Professor Colin Neal* 434, 130–142.
1272 <https://doi.org/10.1016/j.scitotenv.2011.07.069>
- 1273 Muraoka, K., Fukushima, T., 1986. On the box model for prediction of water quality in eutrophic lakes.
1274 *Ecol. Model.* 31, 221–236. [https://doi.org/10.1016/0304-3800\(86\)90065-7](https://doi.org/10.1016/0304-3800(86)90065-7)
- 1275 Na, E.H., Park, S.S., 2006. A hydrodynamic and water quality modeling study of spatial and temporal pat-
1276 terns of phytoplankton growth in a stratified lake with buoyant incoming flow. *Ecol. Model.* 199,
1277 298–314. <https://doi.org/10.1016/j.ecolmodel.2006.05.008>
- 1278 National Academy of Sciences, 1969. Eutrophication: causes, consequences, correctives. *Proceedings of
1279 Madison Symposium, Wisconsin, 11-15 June. 1967.*
- 1280 Newcombe, G., 2012. *International Guidance Manual for the Management of Toxic Cyanobacteria.* *Water
1281 Intell. Online* 11. <https://doi.org/10.2166/9781780401355>
- 1282 Nielsen, A., Trolle, D., Bjerring, R., Søndergaard, M., Olesen, J.E., Janse, J.H., Mooij, W.M., Jeppesen, E.,
1283 2014. Effects of climate and nutrient load on the water quality of shallow lakes assessed through en-
1284 semble runs by PCLake. *Ecol. Appl.* 24, 1926–1944.
- 1285 Nürnberg, G.K., LaZerte, B.D., 2004. Modeling the effect of development on internal phosphorus load in
1286 nutrient-poor lakes. *Water Resour. Res.* 40, W01105. <https://doi.org/10.1029/2003WR002410>
- 1287 Nyholm, N., 1978. A simulation model for phytoplankton growth and nutrient cycling in eutrophic, shallow
1288 lakes. *Ecol. Model.* 4, 279–310. [https://doi.org/10.1016/0304-3800\(78\)90011-X](https://doi.org/10.1016/0304-3800(78)90011-X)

- 1289 Obenour, D.R., Gronewold, A.D., Stow, C.A., Scavia, D., 2014. Using a Bayesian hierarchical model to
1290 improve Lake Erie cyanobacteria bloom forecasts. *Water Resour. Res.* 50, 7847–7860.
1291 <https://doi.org/10.1002/2014WR015616>
- 1292 Ogilvie, S., Mitchell, S., 1995. A model of mussel filtration in a shallow new-zealand lake, with reference to
1293 eutrophication control. *Arch. Hydrobiol.* 133, 471–482.
- 1294 Onderka, M., 2007. Correlations between several environmental factors affecting the bloom events of cyano-
1295 bacteria in Liptovska Mara reservoir (Slovakia)—A simple regression model. *Ecol. Model.* 209,
1296 412–416. <https://doi.org/10.1016/j.ecolmodel.2007.07.028>
- 1297 O’Neil, J.M., Davis, T.W., Burford, M.A., Gobler, C.J., 2012. The rise of harmful cyanobacteria blooms:
1298 The potential roles of eutrophication and climate change. *Harmful Algae* 14, 313–334.
1299 <https://doi.org/10.1016/j.hal.2011.10.027>
- 1300 Ozkundakci, D., Hamilton, D.P., Trolle, D., 2011. Modelling the response of a highly eutrophic lake to re-
1301 ductions in external and internal nutrient loading. *N. Z. J. Mar. Freshw. Res.* 45, 165–185.
1302 <https://doi.org/10.1080/00288330.2010.548072>
- 1303 Paerl, H.W., Huisman, J., 2008. Blooms Like It Hot. *Science* 320, 57–58.
1304 <https://doi.org/10.1126/science.1156721>
- 1305 Paerl, H.W., Paul, V.J., 2012. Climate change: Links to global expansion of harmful cyanobacteria. *Water*
1306 *Res.* 46, 1349–1363. <https://doi.org/10.1016/j.watres.2011.08.002>
- 1307 Paraska, D.W., Hipsey, M.R., Salmon, S.U., 2014. Sediment diagenesis models: Review of approaches, chal-
1308 lenges and opportunities. *Environ. Model. Softw.* 61, 297–325.
1309 <https://doi.org/10.1016/j.envsoft.2014.05.011>
- 1310 Patterson, J., Hamilton, D., Ferris, J., 1994. Modelling of cyanobacterial blooms in the mixed layer of lakes
1311 and reservoirs. *Mar. Freshw. Res.* 45, 829. <https://doi.org/10.1071/MF9940829>
- 1312 Patynen, A., Elliott, J.A., Kiuru, P., Sarvala, J., Ventela, A.M., Jones, R.I., 2014. Modelling the impact of
1313 higher temperature on the phytoplankton of a boreal lake. *Boreal Environ. Res.* 19, 66–78.
- 1314 Peretyatko, A., Teissier, S., Backer, S.D., Triest, L., 2012. Classification trees as a tool for predicting
1315 cyanobacterial blooms. *Hydrobiologia* 689, 131–146. <https://doi.org/10.1007/s10750-011-0803-4>

- 1316 Perga, M.-E., Maberly, S.C., Jenny, J.-P., Alric, B., Pignol, C., Naffrechoux, E., 2016. A century of human-
1317 driven changes in the carbon dioxide concentration of lakes. *Glob. Biogeochem. Cycles* 30, 93–104.
1318 <https://doi.org/10.1002/2015GB005286>
- 1319 Perroud, M., Goyette, S., Martynov, A., Beniston, M., Annevillec, O., 2009. Simulation of multiannual
1320 thermal profiles in deep Lake Geneva: A comparison of one-dimensional lake models. *Limnol.*
1321 *Oceanogr.* 54, 1574–1594.
- 1322 Pers, B., 2005. Modeling the response of eutrophication control measures in a Swedish lake. *AMBIO* 34,
1323 552–558. [https://doi.org/10.1639/0044-7447\(2005\)034\[0552:MTROEC\]2.0.CO;2](https://doi.org/10.1639/0044-7447(2005)034[0552:MTROEC]2.0.CO;2)
- 1324 Pinay, G., Gascuel, C., Menesguen, A., Souchon, Y., Le Moal, M., 2017. L’eutrophisation : manifestations,
1325 causes, conséquences et prédictibilité . Synthèse de l’Expertise scientifique collective. CNRS -
1326 Ifremer - INRA - Irstea, France.
- 1327 Pipp, E., Rott, E., 1995. A phytoplankton compartment model for a small meromictic lake with special refer-
1328 ence to species-specific niches and long-term changes. *Ecol. Model.* 78, 129–148.
1329 [https://doi.org/10.1016/0304-3800\(94\)00123-Y](https://doi.org/10.1016/0304-3800(94)00123-Y)
- 1330 Politi, E., Prairie, Y.T., 2018. The potential of Earth Observation in modelling nutrient loading and water
1331 quality in lakes of southern Quebec, Canada. *Aquat. Sci.* 80, UNSP 8.
1332 <https://doi.org/10.1007/s00027-017-0559-7>
- 1333 Pomati, F., Matthews, B., Seehausen, O., Ibelings, B.W., 2017. Eutrophication and climate warming alter
1334 spatial (depth) co-occurrence patterns of lake phytoplankton assemblages. *Hydrobiologia* 787, 375–
1335 385. <https://doi.org/10.1007/s10750-016-2981-6>
- 1336 Posch, T., Köster, O., Salcher, M.M., Pernthaler, J., 2012. Harmful filamentous cyanobacteria favoured by
1337 reduced water turnover with lake warming. *Nat. Clim. Change* 2, 809–813.
1338 <https://doi.org/10.1038/nclimate1581>
- 1339 Rankovic, V., Radulovic, J., Radojevic, I., Ostojic, A., Comic, L., 2010. Neural network modeling of dis-
1340 solved oxygen in the Gruza reservoir, Serbia. *Ecol. Model.* 221, 1239–1244.
1341 <https://doi.org/10.1016/j.ecolmodel.2009.12.023>

- 1342 Reckhow, K., 1993. A random coefficient model for chlorophyll nutrient relationships in lakes. *Ecol. Model.*
1343 70, 35–50. [https://doi.org/10.1016/0304-3800\(93\)90071-Y](https://doi.org/10.1016/0304-3800(93)90071-Y)
- 1344 Reckhow, K.H., 1994. Water quality simulation modeling and uncertainty analysis for risk assessment and
1345 decision making. *Ecol. Model.* 72, 1–20. [https://doi.org/10.1016/0304-3800\(94\)90143-0](https://doi.org/10.1016/0304-3800(94)90143-0)
- 1346 Recknagel, F., Adrian, R., Koehler, J., Cao, H., 2016. Threshold quantification and short-term forecasting of
1347 *Anabaena*, *Aphanizomenon* and *Microcystis* in the polymictic eutrophic Lake Muggelsee (Germany)
1348 by inferential modelling using the hybrid evolutionary algorithm HEA. *Hydrobiologia* 778, 61–74.
1349 <https://doi.org/10.1007/s10750-015-2442-7>
- 1350 Reynolds, C.S., Irish, A.E., 1997. Modelling phytoplankton dynamics in lakes and reservoirs: the problem of
1351 in-situ growth rates. *Hydrobiologia* 349, 5–17. <https://doi.org/10.1023/A:1003020823129>
- 1352 Reynolds, C. S., Irish, A.E., Elliott, J.A., 2001. The ecological basis for simulating phytoplankton responses
1353 to environmental change (PROTECH). *Ecol. Model.* 140, 271–291.
- 1354 Reynolds, C.S., Irish, A.E., Elliott, J.A., 2001. The ecological basis for simulating phytoplankton responses
1355 to environmental change (PROTECH). *Ecol. Model.* 140, 271–291. [https://doi.org/10.1016/S0304-](https://doi.org/10.1016/S0304-3800(01)00330-1)
1356 [3800\(01\)00330-1](https://doi.org/10.1016/S0304-3800(01)00330-1)
- 1357 Rigosi, A., Fleenor, W., Rueda, F., 2010. State-of-the-art and recent progress in phytoplankton succession
1358 modelling. *Environ. Rev.* 18, 423–440. <https://doi.org/10.1139/A10-021>
- 1359 Riley, M.J., Stefan, H.G., 1988. Minlake: A dynamic lake water quality simulation model. *Ecol. Model.* 43,
1360 155–182. [https://doi.org/10.1016/0304-3800\(88\)90002-6](https://doi.org/10.1016/0304-3800(88)90002-6)
- 1361 Rivera, E.C., de Queiroz, J.F., Ferraz, J.M., Ortega, E., 2007. Systems models to evaluate eutrophication in
1362 the Broa Reservoir, Sao Carlos, Brazil. *Ecol. Model.* 202, 518–526.
1363 <https://doi.org/10.1016/j.ecolmodel.2006.11.016>
- 1364 Riverson, J., Coats, R., Costa-Cabral, M., Dettinger, M., Reuter, J., Sahoo, G., Schladow, G., 2013. Model-
1365 ing the transport of nutrients and sediment loads into Lake Tahoe under projected climatic changes.
1366 *Clim. Change* 116, 35–50. <https://doi.org/10.1007/s10584-012-0629-8>

- 1367 Robertson, D.M., Saad, D.A., 2011. Nutrient Inputs to the Laurentian Great Lakes by Source and Watershed
1368 Estimated Using SPARROW Watershed Models1. *JAWRA J. Am. Water Resour. Assoc.* 47, 1011–
1369 1033. <https://doi.org/10.1111/j.1752-1688.2011.00574.x>
- 1370 Rodriguez Reartes, S.B., Estrada, V., Bazan, R., Larrosa, N., Cossavella, A., Lopez, A., Busso, F., Diaz,
1371 M.S., 2016. Evaluation of ecological effects of anthropogenic nutrient loading scenarios in Los
1372 Molinos reservoir through a mathematical model. *Ecol. Model.* 320, 393–406.
1373 <https://doi.org/10.1016/j.ecolmodel.2015.10.028>
- 1374 Romshoo, S.A., Muslim, M., 2011. Geospatial modeling for assessing the nutrient load of a Himalayan lake.
1375 *Environ. EARTH Sci.* 64, 1269–1282. <https://doi.org/10.1007/s12665-011-0944-9>
- 1376 Rukhovets, L., Astrakhantsev, G., Menshutkin, V., Minina, T., Petrova, N., Poloskov, V., 2003. Develop-
1377 ment of Lake Ladoga ecosystem models: modeling of the phytoplankton succession in the eutrophi-
1378 cation process. I. *Ecol. Model.* 165, 49–77. [https://doi.org/10.1016/S0304-3800\(03\)00061-9](https://doi.org/10.1016/S0304-3800(03)00061-9)
- 1379 Sagehashi, M., Sakoda, A., Suzuki, M., 2001. A mathematical model of a shallow and eutrophic lake (the
1380 Keszthely Basin, Lake Balaton) and simulation of restorative manipulations. *WATER Res.* 35,
1381 1675–1686. [https://doi.org/10.1016/S0043-1354\(00\)00435-8](https://doi.org/10.1016/S0043-1354(00)00435-8)
- 1382 Sahoo, G.B., Luketina, D., 2003. Modeling of bubble plume design and oxygen transfer for reservoir restora-
1383 tion. *Water Res.* 37, 393–401. [https://doi.org/10.1016/S0043-1354\(02\)00283-X](https://doi.org/10.1016/S0043-1354(02)00283-X)
- 1384 Salerno, F., Viviano, G., Carraro, E., Manfredi, E.C., Lami, A., Musazzi, S., Marchetto, A., Guyennon, N.,
1385 Tartari, G., Copetti, D., 2014. Total phosphorus reference condition for subalpine lakes: A compari-
1386 son among traditional methods and a new process-based watershed approach. *J. Environ. Manage.*
1387 145, 94–105. <https://doi.org/10.1016/j.jenvman.2014.06.011>
- 1388 Sarkar, R.R., Chattopadhyay, J., 2003. Occurrence of planktonic blooms under environmental fluctuations
1389 and its possible control mechanism—mathematical models and experimental observations. *J. Theor.*
1390 *Biol.* 224, 501–516. [https://doi.org/10.1016/S0022-5193\(03\)00200-5](https://doi.org/10.1016/S0022-5193(03)00200-5)
- 1391 Scavia, D., Powers, W.F., Canale, R.P., Moody, J.L., 1981. Comparison of first-order error analysis and
1392 Monte Carlo Simulation in time-dependent lake eutrophication models. *Water Resour. Res.* 17,
1393 1051–1059. <https://doi.org/10.1029/WR017i004p01051>

- 1394 Schindler, D.W., 2009. Lakes as sentinels and integrators for the effects of climate change on watersheds,
1395 airsheds, and landscapes. *Limnol Ocean.* 54, 2349–2358.
- 1396 Schindler, D.W., 2006. Recent advances in the understanding and management of eutrophication. *Limnol.*
1397 *Oceanogr.* 51, 356–363.
- 1398 Schnoor, J., O'Connor, D., 1980. A steady-state eutrophication model for lakes. *Water Res.* 14, 1651–1665.
1399 [https://doi.org/10.1016/0043-1354\(80\)90071-8](https://doi.org/10.1016/0043-1354(80)90071-8)
- 1400 Schwalb, A.N., Bouffard, D., Boegman, L., Leon, L., Winter, J.G., Molot, L.A., Smith, R.E.H., 2015. 3D
1401 modelling of dreissenid mussel impacts on phytoplankton in a large lake supports the nearshore
1402 shunt hypothesis and the importance of wind-driven hydrodynamics. *Aquat. Sci.* 77, 95–114.
1403 <https://doi.org/10.1007/s00027-014-0369-0>
- 1404 Schwefel, R., Gaudard, A., Wuest, A., Bouffard, D., 2016. Effects of climate change on deepwater oxygen
1405 and winter mixing in a deep lake (Lake Geneva): Comparing observational findings and modeling.
1406 *WATER Resour. Res.* 52, 8794–8809. <https://doi.org/10.1002/2016WR019194>
- 1407 Seip, K.L., 1991. The ecosystem of a mesotrophic lake-I. Simulating plankton biomass and the timing of
1408 phytoplankton blooms. *Aquat. Sci.* 53, 239–262. <https://doi.org/10.1007/BF00877061>
- 1409 Seo, D.-I., Canale, R.P., 1996. Performance, reliability and uncertainty of total phosphorus models for
1410 lakes—I. Deterministic analyses. *Water Res.* 30, 83–94. [https://doi.org/10.1016/0043-](https://doi.org/10.1016/0043-1354(95)00114-Z)
1411 [1354\(95\)00114-Z](https://doi.org/10.1016/0043-1354(95)00114-Z)
- 1412 Shan, K., Li, L., Wang, X., Wu, Y., Hu, L., Yu, G., Song, L., 2014. Modelling ecosystem structure and
1413 trophic interactions in a typical cyanobacterial bloom-dominated shallow Lake Dianchi, China. *Ecol.*
1414 *Model.* 291, 82–95. <https://doi.org/10.1016/j.ecolmodel.2014.07.015>
- 1415 Shimoda, Y., Arhonditsis, G.B., 2016. Phytoplankton functional type modelling: Running before we can
1416 walk? A critical evaluation of the current state of knowledge. *Ecol. Model.* 320, 29–43.
1417 <https://doi.org/10.1016/j.ecolmodel.2015.08.029>
- 1418 Silva, T.F. das G., Vinçon-Leite, B., Giani, A., Figueredo, C.C., Petrucci, G., Lemaire, B., Sperling, E.V.,
1419 Tassin, B., Seidl, M., Tran Khac, V., Viana, P.S., Viana, V.F.L., Toscano, R.A., Rodrigues, B.H.M.,
1420 Nascimento, N. de O., 2016. Modelagem da Lagoa da Pampulha: uma ferramenta para avaliar o

- 1421 impacto da bacia hidrográfica na dinâmica do fitoplâncton. *Eng. Sanit. E Ambient.* 21, 95–108.
1422 <https://doi.org/10.1590/S1413-41520201600100125692>
- 1423 Simonsen, J.F., Dahl-Madsen, K.I., 1978. Eutrophication Models for Lakes. *Nord. Hydrol.* 9, 12.
- 1424 Singleton, V.L., Rueda, F.J., Little, J.C., 2010. A coupled bubble plume–reservoir model for hypolimnetic
1425 oxygenation. *Water Resour. Res.* 46. <https://doi.org/10.1029/2009WR009012>
- 1426 Smith, S.L., Merico, A., Wirtz, K.W., Pahlow, M., 2014. Leaving misleading legacies behind in plankton
1427 ecosystem modelling. *J. Plankton Res.* 36, 613–620. <https://doi.org/10.1093/plankt/fbu011>
- 1428 Smith, V.H., Joye, S.B., Howarth, R.W., 2006. Eutrophication of freshwater and marine ecosystems. *Limnol*
1429 *Ocean.* 51, 351–355.
- 1430 Smits, J.G.C., van der Molen, D.T., 1993. Application of SWITCH, a model for sediment-water exchange of
1431 nutrients, to Lake Veluwe in The Netherlands. *HYDROBIOLOGIA* 253, 20.
1432 <https://doi.org/10.1007/BF00050749>
- 1433 Snodgrass, W.J., 1987. Analysis of Models and Measurements for Sediment Oxygen Demand in Lake Erie.
1434 *J. Gt. Lakes Res.* 13, 738–756. [https://doi.org/10.1016/S0380-1330\(87\)71688-8](https://doi.org/10.1016/S0380-1330(87)71688-8)
- 1435 Snodgrass, W.J., 1985. Lake Ontario oxygen model. 2. Errors associated with estimating transport across the
1436 thermocline. *Environ. Sci. Technol.* 19, 180–185. <https://doi.org/10.1021/es00132a012>
- 1437 Sondergaard, M., Jeppesen, E., 2007. Anthropogenic impacts on lake and stream ecosystems, and approaches
1438 to restoration. *J. Appl. Ecol.* 44, 1089–1094.
- 1439 Soullignac, F., Vinçon-Leite, B., Lemaire, B.J., Scarati Martins, J.R., Bonhomme, C., Dubois, P., Mezemate,
1440 Y., Tchiguirinskaia, I., Schertzer, D., Tassin, B., 2017. Performance Assessment of a 3D Hydrody-
1441 namic Model Using High Temporal Resolution Measurements in a Shallow Urban Lake. *Environ.*
1442 *Model. Assess.* 22, 309–322. <https://doi.org/10.1007/s10666-017-9548-4>
- 1443 Stansbury, J., Kozimor, L., Admiraal, D., Dove, E., 2008. Water quality modeling of the effects of
1444 macrophytes on dissolved oxygen in a shallow tailwater reservoir. *Lake Reserv. Manag.* 24, 339–
1445 348. <https://doi.org/10.1080/07438140809354844>

- 1446 Stepanenko, V., Mammarella, I., Ojala, A., Miettinen, H., Lykosov, V., Vesala, T., 2016. LAKE 2.0: a model
1447 for temperature, methane, carbon dioxide and oxygen dynamics in lakes. *Geosci. Model Dev.* 9,
1448 1977–2006. <https://doi.org/10.5194/gmd-9-1977-2016>
- 1449 Stepanenko, V.M., Goyette, S., Martynov, A., Perroud, M., Fang, X., Mironov, D., 2010. First steps of a
1450 Lake Model Intercomparison Project: LakeMIP. *Boreal Environ. Res.* 15, 191–202.
- 1451 Stepanenko, V.M., Martynov, A., Jöhnk, K.D., Subin, Z.M., Perroud, M., Fang, X., Beyrich, F., Mironov,
1452 D., Goyette, S., 2012. A one-dimensional model intercomparison study of thermal regime of a shal-
1453 low, turbid midlatitude lake. *Geosci. Model Dev.* 6, 1337–1352. [https://doi.org/10.5194/gmd-6-](https://doi.org/10.5194/gmd-6-1337-2013)
1454 [1337-2013](https://doi.org/10.5194/gmd-6-1337-2013)
- 1455 Stow, C., Carpenter, S., Lathrop, R., 1997. A Bayesian observation error model to predict cyanobacterial
1456 biovolume from spring total phosphorus in Lake Mendota, Wisconsin. *Can. J. Fish. Aquat. Sci.* 54,
1457 464–473. <https://doi.org/10.1139/cjfas-54-2-464>
- 1458 Takkouk, S., Casamitjana, X., 2016. Application of the DYRESM–CAEDYM model to the Sau Reservoir
1459 situated in Catalonia, Spain. *Desalination Water Treat.* 57, 12453–12466.
1460 <https://doi.org/10.1080/19443994.2015.1053530>
- 1461 Takolander, A., Cabeza, M., Leskinen, E., 2017. Climate change can cause complex responses in Baltic Sea
1462 macroalgae: A systematic review. *J. Sea Res.* 123, 16–29.
1463 <https://doi.org/10.1016/j.seares.2017.03.007>
- 1464 Terry, J.A., Sadeghian, A., Lindenschmidt, K.-E., 2017. Modelling Dissolved Oxygen/Sediment Oxygen
1465 Demand under Ice in a Shallow Eutrophic Prairie Reservoir. *Water* 9, 131.
1466 <https://doi.org/10.3390/w9020131>
- 1467 Teruggi, S., Vendegna, V., 1986. Ecological models as support systems to decisions in lake management
1468 planning. *Sci. Total Environ.* 55, 261–273. [https://doi.org/10.1016/0048-9697\(86\)90185-3](https://doi.org/10.1016/0048-9697(86)90185-3)
- 1469 Toffolon, M., Serafini, M., 2013. Effects of artificial hypolimnetic oxygenation in a shallow lake. Part 2:
1470 Numerical modelling. *J. Environ. Manag. Artic.* 114, 530–539.
1471 <https://doi.org/10.1016/j.jenvman.2012.10.063>

- 1472 Trolle, D., Elliott, J.A., Mooij, W.M., Janse, J.H., Bolding, K., Hamilton, D.P., Jeppesen, E., 2014. Advanc-
1473 ing projections of phytoplankton responses to climate change through ensemble modelling. *Environ.*
1474 *Model. Softw.* 61, 371–379. <https://doi.org/10.1016/j.envsoft.2014.01.032>
- 1475 Trolle, D., Hamilton, D.P., Hipsey, M.R., Bolding, K., Bruggeman, J., Mooij, W.M., Janse, J.H., Nielsen, A.,
1476 Jeppesen, E., Elliott, J.A., Makler-Pick, V., Petzoldt, T., Rinke, K., Flindt, M.R., Arhonditsis, G.B.,
1477 Gal, G., Bjerring, R., Tominaga, K., Hoen, J., Downing, A.S., Marques, D.M., Jr, C.R.F.,
1478 Søndergaard, M., Hanson, P.C., 2011a. A community-based framework for aquatic ecosystem mod-
1479 els. *Hydrobiologia* 683, 25–34. <https://doi.org/10.1007/s10750-011-0957-0>
- 1480 Trolle, D., Hamilton, D.P., Pilditch, C.A., Duggan, I.C., Jeppesen, E., 2011b. Predicting the effects of cli-
1481 mate change on trophic status of three morphologically varying lakes: Implications for lake restora-
1482 tion and management. *Environ. Model. Softw.* 26, 354–370.
1483 <https://doi.org/10.1016/j.envsoft.2010.08.009>
- 1484 Trolle, D., Skovgaard, H., Jeppesen, E., 2008. The Water Framework Directive: Setting the phosphorus load-
1485 ing target for a deep lake in Denmark using the 1D lake ecosystem model DYRESM–CAEDYM.
1486 *Ecol. Model.* 219, 138–152. <https://doi.org/10.1016/j.ecolmodel.2008.08.005>
- 1487 Tyler, A.N., Svab, E., Preston, T., Presing, M., Kovacs, W.A., 2006. Remote sensing of the water quality of
1488 shallow lakes: A mixture modelling approach to quantifying phytoplankton in water characterized by
1489 high-suspended sediment. *Int. J. Remote Sens.* 27, 1521–1537.
1490 <https://doi.org/10.1080/01431160500419311>
- 1491 van Puijenbroek, P., Janse, J.H., Knoop, J.M., 2004. Integrated modelling for nutrient loading and ecology of
1492 lakes in The Netherlands. *Ecol. Model.* 174, 127–141.
1493 <https://doi.org/10.1016/j.ecolmodel.2004.01.002>
- 1494 Van Straten, G.T., Keesman, K.J., 1991. Uncertainty propagation and speculation in projective forecasts of
1495 environmental change: A lake-eutrophication example. *J. Forecast.* 10, 163–190.
1496 <https://doi.org/10.1002/for.3980100110>

1497 Vanhuet, H., 1992. Phosphorus eutrophication in the SW Frisian lake district .1. Monitoring and assessment
1498 of a dynamic mass balance model. *Hydrobiologia* 233, 259–270.
1499 <https://doi.org/10.1007/BF00016114>

1500 Varis, O., 1993. Cyanobacteria dynamics in a restored finnish lake - a long-term simulation study.
1501 *Hydrobiologia* 268, 129–145. <https://doi.org/10.1007/BF00014049>

1502 Verhagen, J., 1994. Modeling phytoplankton patchiness under the influence of wind-driven currents in lakes.
1503 *Limnol. Oceanogr.* 39, 1551–1565. <https://doi.org/10.4319/lo.1994.39.7.1551>

1504 Vollenweider, R.A., 1975. Input-output models. With special reference to the phosphorus loading concept in
1505 limnology. *Schweiz. Z. Für Hydrol.* 37, 53–84. <https://doi.org/10.1007/BF02505178>

1506 Vollenweider, R.A., Kerekes, J., 1982. Eutrophication of waters. Monitoring, assessment and control. OECD
1507 Cooperative programme on monitoring of inland waters. OECD, Paris.

1508 Wagner, C., Adrian, R., 2009. Cyanobacteria dominance: Quantifying the effects of climate change. *Limnol.*
1509 *Oceanogr.* 54, 2460–2468. https://doi.org/10.4319/lo.2009.54.6_part_2.2460

1510 Walker, R.R., Snodgrass, W.J., 1986. Model for Sediment Oxygen Demand in Lakes. *J. Environ. Eng.* 112,
1511 25–43. [https://doi.org/10.1061/\(ASCE\)0733-9372\(1986\)112:1\(25\)](https://doi.org/10.1061/(ASCE)0733-9372(1986)112:1(25))

1512 Walsby, A., 2005. Stratification by cyanobacteria in lakes: a dynamic buoyancy model indicates size limita-
1513 tions met by *Planktothrix rubescens* filaments. *NEW Phytol.* 168, 365–376.
1514 <https://doi.org/10.1111/j.1469-8137.2005.01508.x>

1515 Wang, B., Qi, Q., 2018. Modeling the lake eutrophication stochastic ecosystem and the research of its stabil-
1516 ity. *Math. Biosci.* 300, 102–114. <https://doi.org/10.1016/j.mbs.2018.03.019>

1517 Wetzel, R.G., 2001. *Limnology: Lake and River Ecosystems*. Academic Press.

1518 World Commission on Dams, 2000. *Dams and development : a new framework for decision-making*. The
1519 report of the World Commission on Dams.

1520 Wu, Z., Liu, Y., Liang, Z., Wu, S., Guo, H., 2017. Internal cycling, not external loading, decides the nutrient
1521 limitation in eutrophic lake: A dynamic model with temporal Bayesian hierarchical inference. *WA-
1522 TER Res.* 116, 231–240. <https://doi.org/10.1016/j.watres.2017.03.039>

- 1523 Xenopoulos, M.A., Downing, J.A., Kumar, M.D., Menden-Deuer, S., Voss, M., 2017. Headwaters to oceans:
1524 Ecological and biogeochemical contrasts across the aquatic continuum. *Limnol. Oceanogr.* 62, S3–
1525 S14. <https://doi.org/10.1002/lno.10721>
- 1526 Xu, F.-L., Jørgensen, S.E., Kong, X.-Z., He, W., Qin, N., 2014. Development of Ecological Models for the
1527 Effects of Macrophyte Restoration on the Ecosystem Health of a Large Eutrophic Chinese Lake
1528 (Lake Chaohu), in: Jørgensen, SE and Chang, NB and Xu, FL (Ed.), *Ecological Modelling and En-*
1529 *gineering of Lakes and Wetlands, Developments in Environmental Modelling.* ELSEVIER, pp. 337–
1530 373. <https://doi.org/10.1016/B978-0-444-63249-4.00014-2>
- 1531 Xu, F.-L., Jørgensen, S.E., Tao, S., Li, B.-G., 1999. Modeling the effects of ecological engineering on eco-
1532 system health of a shallow eutrophic Chinese lake (Lake Chao). *Ecol. Model.* 117, 239–260.
1533 [https://doi.org/10.1016/S0304-3800\(99\)00005-8](https://doi.org/10.1016/S0304-3800(99)00005-8)
- 1534 Xu, Yunfeng, Ma, C., Liu, Q., Xi, B., Qian, G., Zhang, D., Huo, S., 2015. Method to predict key factors af-
1535 fecting lake eutrophication - A new approach based on Support Vector Regression model. *Int.*
1536 *Biodeterior. Biodegrad.* 102, 308–315. <https://doi.org/10.1016/j.ibiod.2015.02.013>
- 1537 Xu, Y., Schroth, A.W., Isles, P.D.F., Rizzo, D.M., 2015. Quantile regression improves models of lake eu-
1538 trophication with implications for ecosystem-specific management. *Freshw. Biol.* 60, 1841–1853.
1539 <https://doi.org/10.1111/fwb.12615>
- 1540 Xu, Z., Xu, Y.J., 2016. A Deterministic Model for Predicting Hourly Dissolved Oxygen Change: Develop-
1541 ment and Application to a Shallow Eutrophic Lake. *WATER* 8. <https://doi.org/10.3390/w8020041>
- 1542 Yacobi, Y.Z., 2006. Temporal and vertical variation of chlorophyll alpha concentration, phytoplankton pho-
1543 tosynthetic activity and light attenuation in Lake Kinneret: possibilities and limitations for simula-
1544 tion by remote sensing. *J. Plankton Res.* 28, 725–736. <https://doi.org/10.1093/plankt/fbl004>
- 1545 Yao, X., Zhang, Y., Zhang, L., Zhou, Y., 2018. A bibliometric review of nitrogen research in eutrophic lakes
1546 and reservoirs. *J. Environ. Sci.* 66, 274–285. <https://doi.org/10.1016/j.jes.2016.10.022>
- 1547 Yi, X., Zou, R., Guo, H., 2016. Global sensitivity analysis of a three-dimensional nutrients-algae dynamic
1548 model for a large shallow lake. *Ecol. Model.* 327, 74–84.
1549 <https://doi.org/10.1016/j.ecolmodel.2016.01.005>

- 1550 Zhang, H., Culver, D.A., Boegman, L., 2008. A two-dimensional ecological model of Lake Erie: Application
1551 to estimate dreissenid impacts on large lake plankton populations. *Ecol. Model.* 214, 219–241.
1552 <https://doi.org/10.1016/j.ecolmodel.2008.02.005>
- 1553 Zhang, H., Hu, W., Gu, K., Li, Q., Zheng, D., Zhai, S., 2013. An improved ecological model and software
1554 for short-term algal bloom forecasting. *Environ. Model. Softw.* 48, 152–162.
1555 <https://doi.org/10.1016/j.envsoft.2013.07.001>
- 1556 Zhang, X., Recknagel, F., Chen, Q., Cao, H., Li, R., 2015. Spatially-explicit modelling and forecasting of
1557 cyanobacteria growth in Lake Taihu by evolutionary computation. *Ecol. Model.* 306, 216–225.
1558 <https://doi.org/10.1016/j.ecolmodel.2014.05.013>
- 1559

Continent	Number of publications	Country	Number of publications	Lake name	Area (km ²)	Number of publications
North America	94	USA-Canada	62	Great lakes	244 000	47
Asia	75	China	51	Lake Erie	25 700	27
Western Europe	20	USA	39	Lake Taihu	2 250	26
Northern Europe	19	Netherlands	10	Lake Ontario	19 000	13
Eastern Europe	7	Japan	8	Lake Michigan	58 000	11
Southern Europe	6	Finland	7	Lake Superior	82 000	9
Oceania	6	Canada	7	Lake Dianchi	298	9
Southern Europe	5	Israel	6	Lake Washington	88	8
Africa	5	United Kingdom	5	Lake Huron	60 000	6
		Hungary	5	Lake Kinneret	166	6
		New-Zealand	4	Lake Balaton	592	5
		Estonia-Russia	3	Lake Veluwe	30	5
		Greece	3	Lake Chaohu	760	5
		Switzerland	3	Lake Okeechobee	1891	4
		Germany	3	Lake Peipsi	3 555	3
		Turkey	3	Lake Bassenthwaite	5	3
		Russia	3	Lake Columbia	3	3
				Lake Spokane	19	3
				Lake Kasumigaura	220	3

Table 1. Number of publications depending on the continent, the country and the name of the studied lake. Only the countries and the lakes that have been found in three or more than three publications are listed.

General Categories	records	% of 438
Science technology	435	99.3
Life sciences biomedicine	363	82.9
Physical sciences	154	35.2
Technology	99	22.6
Social sciences	2	0.5
Research Areas	records	% of 438
Environmental Sciences and Ecology	272	62.1
Marine and Freshwater biology	141	32.2
Water resources	101	23.1
Engineering	86	19.6
Geology	30	6.8
Oceanography	22	5.0
Mathematics	10	2.3
Computer science	9	2.1
Journal Titles	records	% of 438
Ecological modelling	70	16.0
Hydrobiologia	25	5.7
Journal of great lakes research	25	5.7
Water research	18	4.1
Water science and technology	13	3.0
Limnology and oceanography	12	2.7
Water resources research	11	2,5
Lake reservoir management	11	2,5
Ecological engineering	8	1.8
Freshwater biology	7	1.6
Science of the Total Environment	7	1.6

Table 2. Repartition of the publications according to their general categories, their research areas and the journal title (provided by Web of Science). Only the research areas (respectively the journal titles) that represent more than 2% (respectively 1.5%) of the bibliographic corpus are listed.

Study sites		Objectives		What is represented in the model		Study of the impact of ...	
226	lake	54	management	117	phosphorus	33	load
213	water	49	simulation	115	phytoplankton	32	environment
147	eutrophic	31	prediction	74	nutrient	31	climate
55	reservoir	22	restoration	56	sediment	26	temperature
46	river			46	nitrogen	22	light
39	shallow	Methods		46	oxygen	on ...	
27	Erie	229	model	44	chlorophyll	97	water quality
25	fresh water	21	regression	35	cyanobacteria	64	dynamics
24	bay	21	sensitivity analysis	34	iron	47	ecosystem
21	great lakes			27	algae	37	growth
				23	zooplankton	29	blooms

Table 3. Classification of keywords according to the number of publications in which they appear.

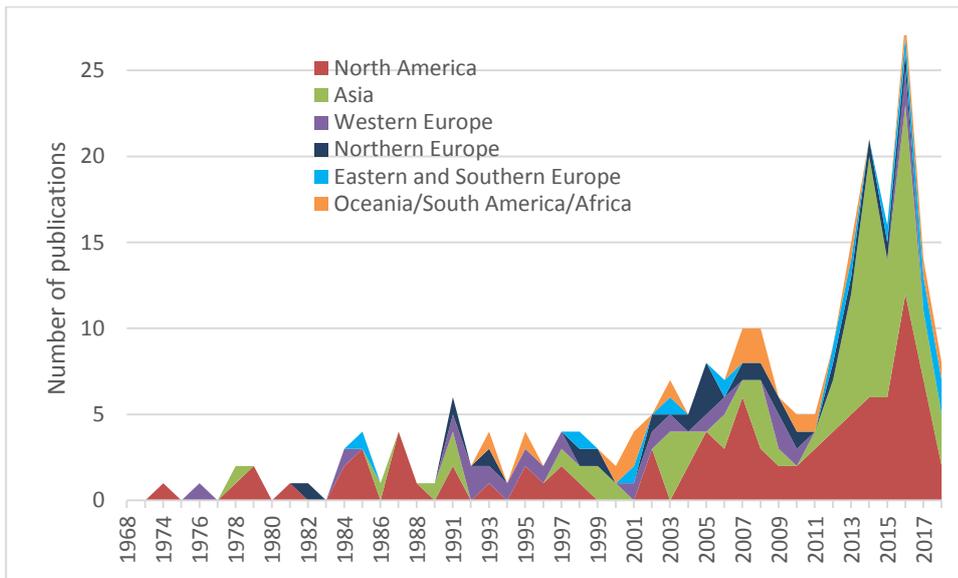
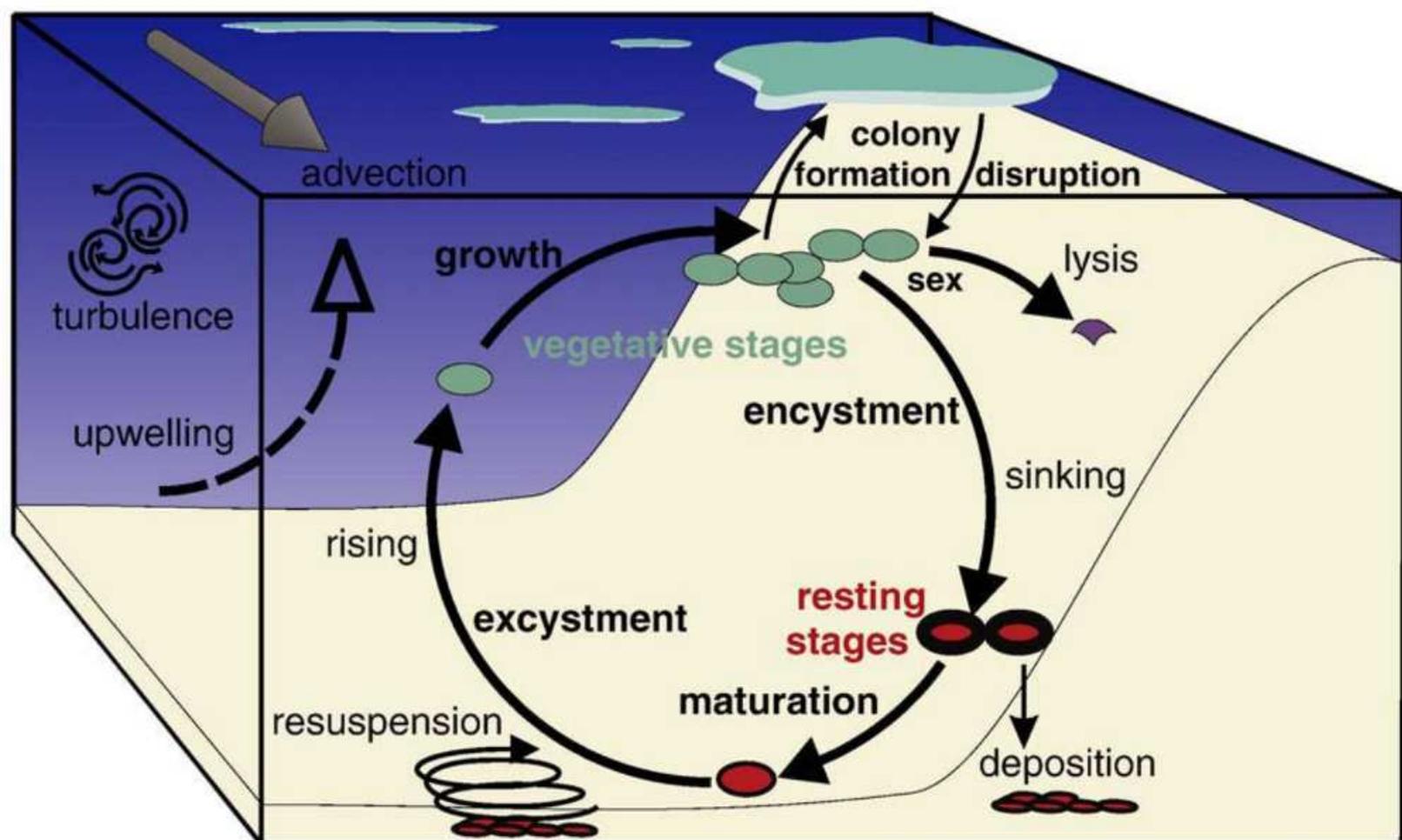


Figure 1. Time evolution of the number of publications according to the continent of the studied lake.

Figure

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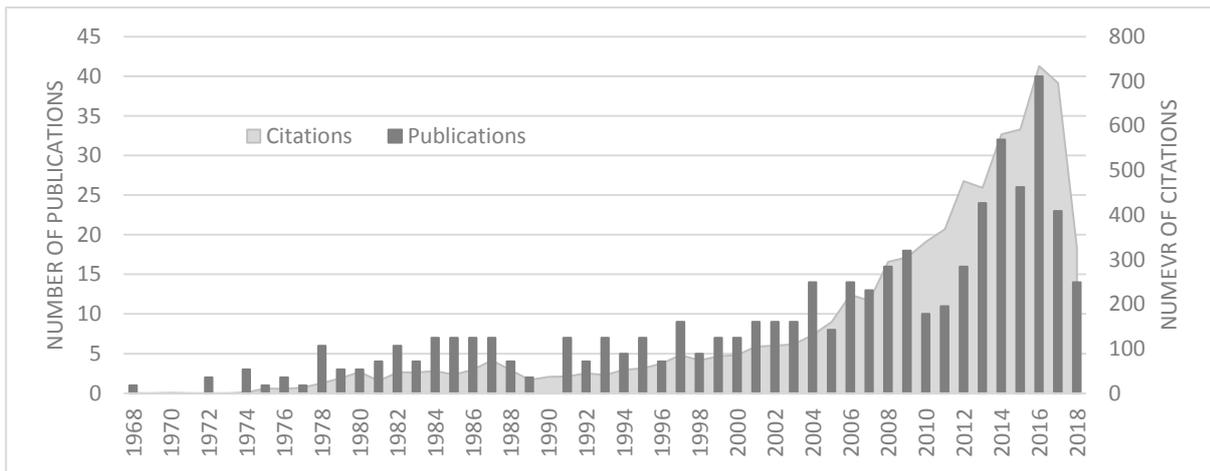


Figure 3. . Number of publications and citations per year, based on the ISI Web of Science citation report.

Highlights

- Lake eutrophication models applied to study sites with management objectives
- Focus on process-based models and cyanobacteria dynamics
- Coupling of hydrodynamics and ecological processes
- Comparison of model results to field data
- Review based on a validated methodology of Scientific Collective Expertise

