

1 **Adaptive forecasting of phytoplankton communities**

2 *Trevor Page^{1**}, Paul J Smith^{1,3}, Keith J Beven¹, Ian D Jones², J Alex Elliott², Stephen C Maberly², Eleanor B*
3 *Mackay², Mitzi De Ville² and Heidrun Feuchtmayr².*

4 ¹ *Lancaster Environment Centre, Library Avenue, Lancaster University, Lancaster, LA1 4YQ, UK.*

5 ² *Lake Ecosystems Group, Centre for Ecology & Hydrology, Lancaster Environment Centre, Library*
6 *Avenue, Bailrigg, Lancaster, LA1 4AP, UK.*

7 ³ *ECMWF, Shinfield Park, Reading, RG2 9AX, UK*

8 **** Corresponding Author:** t.page@lancaster.ac.uk

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10 cyanobacteria, PROTECH.

11 **Abstract**

12 The global proliferation of harmful algal blooms poses an increasing threat to water resources, recreation
13 and ecosystems. Predicting the occurrence of these blooms is therefore needed to assist water managers
14 in making management decisions to mitigate their impact. Evaluation of the potential for forecasting of
15 algal blooms using the phytoplankton community model PROTECH was undertaken in pseudo-real-time.
16 This was achieved within a data assimilation scheme using the Ensemble Kalman Filter to allow
17 uncertainties and model nonlinearities to be propagated to forecast outputs. Tests were made on two
18 mesotrophic lakes in the English Lake District, which differ in depth and nutrient regime. Some forecasting
19 success was shown for chlorophyll *a*, but not all forecasts were able to perform better than a persistence
20 forecast. There was a general reduction in forecast skill with increasing forecasting period but forecasts
21 for up to four or five days showed noticeably greater promise than those for longer periods. Associated

22 forecasts of phytoplankton community structure were broadly consistent with observations but their
23 translation to cyanobacteria forecasts was challenging owing to the interchangeability of simulated
24 functional species.

25 **1 Introduction**

26 Algal blooms are a global problem affecting water resources, recreation and ecosystems (Carmichael,
27 1992; Smith, 2003; World Health Organization, 1999). These problems are particularly acute when
28 cyanobacterial species dominate because of the risk of toxin production that can cause adverse effects to
29 humans and wildlife (Metcalf and Codd, 2009). In addition, water supply companies face associated
30 problems such as poor taste and odour and, in extreme cases, high concentrations of algal-derived toxins
31 which are costly to manage (Pretty *et al.*, 2003; Dodds *et al.*, 2009; Michalak, 2016). Costs associated with
32 implementation of management strategies are growing because of increased bloom frequency (Ho and
33 Michalak, 2015) and because of the effects of widespread nutrient enrichment and climate change (Paerl
34 and Huisman, 2008; Brookes and Carey, 2011; Rigosi *et al.* 2014). As a result, there is an urgent need for
35 reliable predictions of algal bloom formation to enable timely management interventions to be
36 implemented.

37 Forecasting algal blooms in lakes is relatively new (Kim *et al.*, 2014) but is increasingly becoming a
38 requirement for lake and reservoir managers (Huang *et al.*, 2013; Recknagel *et al.* 2014; Xiao *et al.*, 2017)
39 to help inform decisions regarding timely and cost-effective management interventions. The fact that
40 limnology is rapidly becoming data-rich (Marcé *et al.*, 2016; Xiao *et al.*, 2014) means that effective real-
41 time forecasts are increasingly more feasible. However, forecast simulations will be inherently uncertain
42 for a number of reasons including input data resolution and simplifications in model process
43 representation. These uncertainties have implications for the accuracy and reliability of a forecast and
44 therefore effort is required to allow for modelling uncertainty. Data assimilation (DA) is one approach to

45 reducing forecast uncertainty but has, to date, received relatively little attention for forecasting
46 phytoplankton community dynamics. There is hence a need to test different DA methodologies across
47 different lake systems and different models.

48 There are still relatively few studies for operational lake forecasting systems and various approaches have
49 been taken such as using: Ensemble Kalman Filter (EnKF; Evensen, 1994) schemes and physically-based
50 simulation models (e.g. Allen *et al.*, 2003, Huang *et al.* 2013 and Kim *et al.*, 2014); evolutionary
51 computation (Recknagel *et al.*, 2014; Ye *et al.*, 2014); Lagrangian particle tracking model methods (Rowe
52 *et al.*, 2016); and a combination of wavelet analysis and neural networks (Luo *et al.*, 2011; Xiao *et al.*,
53 2017). The EnKF has been developed to deal with highly non-linear model dynamics which cannot be
54 represented well using the traditional Kalman Filter. Phytoplankton population dynamics are highly non-
55 linear with multiple modes of behaviour that can respond rapidly to threshold-type effects and are prone
56 to rapid changes in their physical and chemical environment (e.g. water temperature, light levels and
57 available nutrients). This makes the EnKF a suitable choice to exploring algal bloom forecasting when
58 coupled with a phytoplankton community model.

59 Here we assess our ability to make pseudo-real-time forecasts of phytoplankton communities in two lakes
60 in the English Lake District in the north west of England, which are prone to cyanobacteria blooms during
61 the summer. Forecasts were made using a modified version of the phytoplankton community model
62 PROTECH (Reynolds *et al.*, 2001) within a DA scheme using the EnKF. The version of PROTECH employed
63 is appropriate for this problem as it is intermediate in its complexity between physically-based coupled 3-
64 dimensional hydrodynamic-biochemical models and more simplistic “black box models” which have both
65 been used in this context. More complex models are extremely computationally expensive in forecasting
66 (Huang *et al.*, 2012; Recknagel, *et al.*, 2014), such that only a limited number of ensemble members can
67 be used (Kim *et al.*, 2014); simple black box models may not be able to represent phytoplankton

68 community dynamics driven by ecological strategies that are represented in phytoplankton community
69 models such as PROTECH.

70 We aimed to determine the efficacy of phytoplankton community forecast simulations, evaluate the EnKF
71 as a DA strategy and investigate the ensemble size required for making consistent forecasts. Ultimately,
72 success will rely on the modelling strategy being sufficiently effective to capture the necessary short-term
73 phytoplankton community dynamics, given the available meteorological forecasts and limitations
74 associated with driving data. Demonstrating the efficacy of the approach therefore requires a robust
75 appraisal procedure with predictions tested qualitatively and quantitatively against appropriate
76 benchmarks. This approach allows other pertinent questions to be investigated; namely, how does
77 forecasting reliability diminish with time-scale of forecast and, most pertinently, what can be learnt from
78 any forecasting failure regarding future model development and optimisation of monitoring strategies.

79 **2 Methods**

80 **2.1 Study lakes**

81 This study considers two lakes in the English Lake District of North West England with differing depths and
82 nutrient regimes (Table 1). The catchments associated with each of the lakes are predominantly hill land,
83 rough-grazed by sheep throughout the year and contain towns and villages that are tourist destinations
84 and are hence associated with seasonal increases in lake nutrient inputs. Windermere is England's largest
85 natural lake and comprises two basins connected at a shallow region approximately halfway along its main
86 axis. The two basins are usually considered separately as they have different characteristics: both basins
87 are monomictic and mesotrophic, but only the south basin was modelled in this study. Esthwaite Water
88 is a small, generally monomictic and occasionally dimictic, lake that has been subject to eutrophication
89 for many decades because of elevated phosphorus levels (Bennion *et al.*, 2000; Dong *et al.*, 2012):
90 cyanobacterial blooms are common in the summer to early autumn. Previous work has shown that

91 internal sources from the lake sediment form an important component of the P budget of the lake (Hall
92 *et al.* 2000; Heaney *et al.*, 1992 and Mackay *et al.*, 2014).

93 **2.2 Data**

94 **2.2.1 Forcing inputs: meteorological forecasts**

95 The primary forcing inputs were meteorological forecasts provided by the European Centre for Medium-
96 term Weather Forecasts (ECMWF) Ensemble Prediction System. The 10-day-ahead forecasts include an
97 ensemble of 50 simulations from perturbed initial states (at 32 km² resolution) and stochastic
98 perturbations of model parameters (see Buizza *et al.*, 1999 and Ollinaho *et al.*, 2016). The re-initialisation
99 of model states in the ECMWF forecasting system is implemented using a higher resolution 3-hour
100 forecast each day. As this re-initialisation is repeated each day, and as perturbations are random, there is
101 no specific relationship between individual ensemble members in subsequent days. The forecast
102 associated with each ensemble member was hence treated as independent from prior forecasts for this
103 study. Daily averages of forecasts were used (i.e. the average of 3-hourly forecasts for days 1-6 and of 6-
104 hourly forecasts day 6-10) for consistency with the daily timestep of PROTECH. Historic forecasts were
105 obtained for 2008, 2009 and 2010 and used in pseudo-real-time. Given the scale of the forecast grid, each
106 forecast variable was “downscaled” to local data as described in the next section.

107 **2.2.2 Sampling meteorological forecasts**

108 Downscaling relationships were developed for air temperature, wind speed, precipitation, cloud cover,
109 relative humidity and solar radiation (Table 2). For air temperature, a relationship was identified between
110 forecasted temperatures and observed temperatures using linear regression. Residuals from this initial
111 analysis helped identify an additional hysteretic relationship between forecasted and observed
112 temperatures, which was attributed to a lake thermal effect; this effect was implemented as an additional

113 correction for each day of the year. Similarly, wind speed was corrected using a linear correction factor
114 coupled with an additional correction based upon wind direction; this was required owing to complex
115 mountainous topography and lake-axis orientation. A wind-rose with sectors of 30 degrees was used to
116 classify forecasted wind speeds and a sector-specific correction was applied. The uncertainty associated
117 with the corrections was represented by fitting a gamma distribution to the data in each sector. All other
118 variables (precipitation, cloud cover, relative humidity and solar radiation), were corrected using a
119 correction multiplier identified using linear regression, without propagating the uncertainty in the
120 relationship. The uncertain relationships for air temperature and wind speed were resampled as
121 perturbations of the ensemble members allowing investigation of the effect of different ensemble sizes.

122 **2.2.3 Nutrient Inputs**

123 Knowledge of diffuse nutrient inputs for the study lakes is relatively poor. Observations available were
124 from approximately monthly frequency routine monitoring and did not cover all river inputs. Both lakes
125 are also impacted by point sources from waste water treatment works (WwTW) and Esthwaite is subject
126 to significant internal P fluxes (Mackay *et al.*, 2014). Diffuse nutrient inputs and WwTW inputs (where
127 included) were treated as reported by Page *et al.* (2017) and these inputs were modified by a
128 multiplicative parameter included in the EnKF scheme (Table 4). For Windermere, upstream lake inputs
129 of nutrients (and chlorophyll *a*) were treated as reported by Page *et al.* (2017) but were not included in
130 the EnKF scheme.

131 **2.2.4 Data for assimilation and evaluation of forecasts**

132 Specific years where the observed data were of the highest frequency, were chosen to test the DA
133 strategy. High frequency (4 minute) data from the automatic lake monitoring systems (Madgwick *et al.*,
134 2006; Mackay *et al.*, 2014) were available and were aggregated to daily values. The variables used for
135 DA are listed in Table 3. The “observed” temperatures for the epilimnion (T_e) and hypolimnion (T_h) used

136 to compare with the modelled variables for these layers were calculated as volume-weighted averages
137 of thermistor chain data, using the simulated epilimnetic depth to delineate the hypolimnion and
138 epilimnion. The “observed” epilimnetic depth (D_e) was estimated using a density gradient method (e.g.
139 see Read *et al.*, 2011). In addition to the automatic monitoring, routine monitoring was carried out at
140 the buoy location at a frequency of approximately every 14 days and included chlorophyll *a*,
141 phytoplankton species “counts”, soluble reactive phosphorus (SRP), dissolved inorganic nitrogen (DIN)
142 and silica (SiO_2) (Table 3). These observations were derived from a water sample at the buoy location
143 integrated over 0-7 m depth (Windermere) or 0-5 m depth (Esthwaite Water) (Maberly *et al.*, 2010).

144 **2.3 Modelling methodology**

145 The modelling strategy employed was designed to represent the different facets of the forecasting system
146 as simply as possible to reduce computational burden, whilst retaining the requirement to explicitly
147 simulate phytoplankton community structure and, specifically, to estimate the likely concentrations of
148 cyanobacteria given the simulated community structure. Thus, the catchment-lake system was simulated
149 using a suite of models of differing complexity from purely data-based (statistically estimated) transfer
150 function (TF) models and process-based models which are consistent, in their complexity, with the
151 available data. A schematic of how the models were combined in the forecasting system is presented in
152 Figure 1 and each model is described in this section. The modelling system is structured around the
153 rationale that epilimnetic depth must be estimated as accurately as possible so that the phytoplankton
154 model, PROTECH, is more likely to provide good estimates of phytoplankton community structure. In
155 PROTECH, community structure is simulated using functional algal types as classified by Reynolds (1988)
156 and as outlined in the next section. The simple conceptual model that estimates epilimnetic depth is a
157 heat energy “balance” model that requires estimates of epilimnetic temperature and energy fluxes to the
158 epilimnion, including those associated with river inflows and outflows.

159 The TF models, epilimnetic depth model and PROTECH are run sequentially; the TF and epilimnetic depth
160 models provide forecast estimates of river flow, epilimnetic depth, epilimnetic temperature and
161 hypolimnetic temperature as inputs to PROTECH. Data assimilation is employed for the two primary
162 models (the epilimnetic depth model and PROTECH) using two separate EnKF schemes that assimilate
163 observations at different intervals; the epilimnetic depth model scheme assimilates epilimnetic depth and
164 epilimnetic temperature estimates as well as hypolimnetic temperature estimates on a daily basis and the
165 scheme for PROTECH assimilates nutrient and chlorophyll *a* concentrations approximately every 14 days.

166 **2.3.1 The PROTECH model**

167 PROTECH (Reynolds *et al.*, 2001) is a lake phytoplankton community model that runs on a daily time-step.
168 It is a 1-dimensional model where the lake is represented by horizontal layers. In the model representation
169 all layers are assumed to be fully mixed throughout the epilimnion. River inputs drive fluxes of diffuse
170 nutrients as well as the flushing of phytoplankton. Upstream lake inputs are treated as river inputs but
171 are given the phytoplankton concentrations associated with the upstream lake, where data are available.

172 Underwater light for model layer *i* is calculated using:

$$173 \quad l_i = I_{surf} \cdot e^{(-\varepsilon \cdot d_i)} \quad (1)$$

174
175 Where: *I_{surf}* is the daily surface light flux, *d* is the depth from the lake surface, ε is the light extinction
176 coefficient resulting from the sum of lake-specific abiotic water attenuation (ε_b) and the extinction of light
177 associated with the concentration of phytoplankton at each timestep multiplied by the parameter ε_a . In
178 the layers from the surface to the epilimnetic depth, the available light is represented by the geometric
179 mean of the epilimnetic layers and hence assumes that phytoplankton spend an equal time in each layer
180 at each timestep. Phytoplankton population dynamics are simulated using the following equation which

181 describes the change in chlorophyll *a* concentration (*X*) of each phytoplankton species selected to
182 represent the algal community (Reynolds *et al.*, 2001):

$$183 \quad \frac{\Delta X}{\Delta t} = (r' - S - G - F) \cdot X \quad (2)$$

184 where *r'* is the growth rate, *S* is settling loss, *G* is a grazing loss and *F* is the loss due to flushing. The growth
185 rate is defined for each layer using:

$$186 \quad r' = \min\{r'_{(\theta)}, r'_{(P)}, r'_{(N)}, r'_{(Si)}\} \quad (3)$$

187 where *r'_{(θ,l)}* is the growth rate at a given temperature (*θ*) and daily photoperiod (*l*) and *r'_{P}*, *r'_{N}*, *r'_{Si}* are the
188 growth rates determined by phosphorus, nitrogen and silica concentrations. The final growth rate (*r'_{corr(θ,l)}*)
189 is a corrected rate allowing for dark respiration using equation 4. This is required as the model growth
190 equations are net of basal metabolism but not dark respiration burden.

$$191 \quad r'_{corr(\theta,l)} = R_{d(\theta)} \cdot r'_{(\theta,l)} - (1 - R_{d(\theta)}) \cdot r'_{(\theta,l)} \quad (4)$$

192 Where *R_{d(θ)}* is the dark respiration rate at temperature *θ*.

193 PROTECH simulates the dynamics of the species chosen to represent the phytoplankton community of a
194 given lake. Species are represented by their morphology, nutrient requirements (i.e. silica requirement
195 and nitrogen fixing ability) and their vertical movement strategies. The number of species simulated is
196 nominally eight (although unlimited) and they are chosen to represent the dominant functional types of
197 the system. Simulations hence represent the behaviour of the functional algal community rather than the
198 dynamics of specific species. The C-S-R functional phytoplankton classification of Reynolds (1988) is used
199 to classify phytoplankton into morphologically defined groups relating to broad ecological strategies. The
200 primary groups are: C-types, which are invasive, ecological pioneers that are small with high surface-to-
201 volume ratios (e.g. *Chlorella*, and *Plagioselmis*); S-types which are 'stress tolerators' that tolerate relatively

202 low nutrient availability and strong stratification (e.g. *Woronichinia*, *Microcystis* and *Oocystis*); and R-types
203 which can harvest sufficient light at low levels to be able to maintain growth and are hence tolerant of
204 well-mixed, intermittently insolated environments (e.g. *Asterionella*, *Aulacoseira* and *Planktothrix*). Also
205 present, but less important for the lake-years studied here, are CS-types, whose characteristics are
206 intermediate between those of C and S species (e.g. *Dolichospermum*, *Aphanizomenon* and *Ceratium*) and
207 CSR-types (e.g. *Cryptomonas*) that are intermediate between C-, S- and R-types. The eight phytoplankton
208 used in each lake for this study are presented in Table Supp. 2.

209 2.3.2 Epilimnetic depth model

210 As a way of reducing computational burden, a simplified representation of lake thermal structure was
211 employed to estimate epilimnetic depth (D_e). The simplified model works on the basis of *independent*
212 estimates of epilimnetic temperature and lake heat energy fluxes. The estimate of epilimnetic
213 temperature (T_e) uses a TF model (see Section 2.3.3) with inputs of air temperature (T_a), solar radiation,
214 wind speed (W_s) and D_e . Air temperature, solar radiation and wind speed are derived from the forecasts
215 and D_e estimates are from the previous simulation timestep. The independent estimates of heat energy
216 fluxes are calculated using the PROTECH energy flux function (see Reynolds *et al.*, 2001) for each timestep
217 using T_e , river temperature and flow magnitude, day length, cloud cover, T_a , Relative Humidity and W_s .
218 These two independent estimates are “balanced” to obtain hypolimnetic volume (V_h) using:

$$219 \quad V_h = \frac{E_{\Delta T}}{\Delta T \cdot C_w \cdot \rho_w} \quad (5)$$

220 where, $E_{\Delta T}$ is the heat energy associated with ΔT (the difference between T_e and the hypolimnetic
221 temperature, T_h), C_w is the specific heat capacity of water, ρ_w is the density of water. Equation 5 is solved
222 to find V_h where: $\Delta T \cdot C_w \cdot \rho_w \cdot V_h \approx E_{\Delta T}$. Subsequently, the epilimnetic volume (V_e) and hence epilimnetic
223 depth (D_e) are estimated by difference:

224
$$V_e = V_t - V_h \tag{6}$$

225 where V_t is the total lake volume. The requirement for ΔT is satisfied by calculating T_h using:

226
$$T_h = \frac{E_{th}}{C_w \cdot \rho_w \cdot V_t} \tag{7}$$

227 where: E_{th} is the “background” heat energy in the lake (associated with T_h and V_t , as defined by Eqn. 7).

228 During the forecast period, E_{th} remains at its previous value until updated during the data assimilation

229 step. This treatment of E_{th} neglects the explicit downward transfer of energy from $E_{\Delta T}$ to E_{th} for forecasting

230 and assumes that these are negligible over this timescale: energy is, however, explicitly transferred

231 downwards each time temperatures are updated during data assimilation. The sequence of calculations

232 for each forecast timestep is:

- 233 1. Estimate lake surface temperature using TF model
- 234 2. Update $E_{\Delta T}$
- 235 I. Radiative energy fluxes
- 236 II. River/upstream lake fluxes
- 237 • Estimate river input volume using TF model
- 238 • Estimate river temperature using TF model
- 239 • Assume upstream lake temperature = modelled lake temperature
- 240 III. If $E_{\Delta T} < 0$ loose energy from E_h (minimum energy set to 0°C)
- 241 3. Estimate T_h from E_{th}
- 242 4. If $E_{\Delta T} > 0$ and If $T_e - T_h$ is greater than a threshold parameter (nominally set to 1°C) estimate
- 243 epilimnetic depth by solving for the volume of water required to match $E_{\Delta T}$ given ΔT :
- 244 subsequently estimate V_e and hence D_e by difference.
- 245 5.

246 2.3.3 Transfer Function models

247 Transfer Function (TF) models were used to estimate lake surface temperature, river temperature and
248 river inflows and outflows. Each model is a discrete-time TF identified directly from the available data.
249 Both the model structures and parameters were identified using the Refined Instrumental Variable (RIV)
250 algorithm (Young, 2015) implemented within the CAPTAIN Toolbox for Matlab™ (Taylor *et al.*, 2007). The
251 resulting model structures and parameter values are presented in Section (Supp. 1) and are either single
252 input- or multi-input, single-output first order models of the general form:

$$253 \quad y_t = \frac{B_1(z-1)}{A(z-1)} U_1 + \frac{B_2(z-1)}{A(z-1)} U_2 + \dots + \frac{B_n(z-1)}{A(z-1)} U_n \quad (8)$$

254 where, y_t is the variable being estimated at time t , U_{1-n} are model input vectors, $A(z-1)$ and $B_n(z-1)$
255 are the model coefficients (polynomials in the backward shift operator: defined by $y_t z^{-1} = y_{t-1}$) that
256 number 1 to n in the case of B but note that in this form for MISO (multi-input single-output) TF the
257 denominator (A) is common to all n TF elements.

258 2.3.4 The Ensemble Kalman Filter

259 The EnKF is a sequential Monte Carlo method which uses a stochastic ensemble of model simulations, and
260 stochastic forcing, to propagate estimates of model states and (or) parameter values between assimilation
261 timesteps. As the ensemble of model simulations is used in place of the linear propagation of an error
262 covariance matrix (as in the traditional Kalman Filter), non-linear model dynamics are retained during
263 model evolution and uncertainties are represented by the variation of the ensemble. When observations
264 are available, each ensemble member is updated individually using a linear update equation (Eqn. 9) which
265 relies on the assumption that the relationship between states and parameters can be described by
266 multivariate Gaussian distributions. Rather than resampling the posterior distributions of the updated

267 ensemble, the EnKF uses each updated ensemble member such that some of the non-Gaussian properties
268 of the forecast are retained (Evenson, 2009). The procedure for the scheme is as follows:

269 1. The EnKF is initialised with an N number ensemble size, sampling states and parameters from *a priori*
270 specified distributions (see below for specific details of this study) and N simulations for the forecast
271 period are carried out. Where parameters are varied as part of the EnKF scheme, they are appended to
272 the state matrix to give a state-parameter matrix.

273 2. When observed data are available for assimilation:

274 I. Apply a linear covariance inflation factor (I) to each of the i states and parameters to reduce the
275 tendency for low ensemble covariance and for spurious correlations associated with small
276 ensemble size (Anderson, 2007; Anderson and Anderson, 1999; Evenson, 2009):

277

$$278 \quad \varphi_{j,i}^a = I. (\varphi_{j,i}^a - \overline{\varphi_i^a}) + \overline{\varphi_i^a} \quad (9)$$

279

280 II. Generate N perturbations of the observations (Y); it is essential that the uncertainty associated
281 with the observations is sampled from a distribution with mean equal to the observed value and
282 covariance (P^e) to avoid bias in the update (Evenson, 2009) and to reduce further the tendency
283 for the updated ensemble to have very low covariance (Moradkhani *et al.*, 2005).

284

285 III. Update the model states and parameters individually for the j^{th} ensemble member. This is done
286 proportionally to the deviation of the states in the forecasted state-parameter matrix (φ^f) from
287 the vector of perturbed observations and the Kalman gain matrix (K): note that the timestep
288 suffix is omitted for clarity in the following equations:

289

290
$$\varphi^a = \varphi^f + (K(Y) - H\varphi^f) \tag{10}$$

291 where, φ^a is the vector of updated states/parameters and H is a matrix that maps the model
292 states to the observed states. The appended parameters are updated using the cross-covariance
293 between the predicted states and parameters. The Kalman gain matrix is calculated using:

294
$$K = P_\varphi^f H^T (H(P_\varphi^f)H^T + P^e)^{-1} \tag{11}$$

295 where, P_φ^f is the covariance matrix for the ensemble of forecasted state-parameter matrix.

296 IV. Apply any constraints on states and (or) parameter distributions (e.g. to keep them within
297 physically reasonable ranges). This was implemented using a resampling scheme where if any
298 state/parameter violated specified constraints (Table 4), the ensemble was resampled using a
299 truncated distribution for that state/parameter in conjunction with a Gaussian copula to retain
300 the ensemble’s covariance structure.

301
302 V. Make N number of simulations for the next forecast period using the updated state-parameter
303 matrix.

304 **2.3.5 Ensemble Kalman Filter scheme: Epilimnetic model**

305 As the epilimnetic model is very simple, all the main model states were used in the EnKF scheme. The
306 states T_e , T_h and D_e were updated using a daily assimilation frequency for the epilimnetic depth model.
307 The “observed” values of these states are those estimated and described above.

308 **2.3.6 Ensemble Kalman Filter scheme: PROTECH**

309 The choice of states and parameters included in the PROTECH EnKF scheme was made based on
310 uncertainty and sensitivity analyses reported by Page *et al.* (2017). The Page *et al.*, study, which included

311 the lakes studied here, identified that the main challenges for forecasting were uncertainties associated
312 with: representing phytoplankton exposure to light and nutrient inputs (particularly phosphorus). The DA
313 scheme was therefore defined to include the main model states, SRP, DIN, SiO₂ and chlorophyll *a*, as well
314 the parameters associated with modifying nutrient inputs and underwater light (Table 4). These were
315 updated at an approximately 14-day frequency set by the monitoring data. For Windermere, both point
316 source (WwTW_{*i*}) and diffuse SRP inputs (P_{fact}) parameters were included in the DA scheme; for Esthwaite
317 Water only the parameter modifying the diffuse SRP inputs was included as simulations which included a
318 simplified representation of sediment-derived SRP inputs did not provide improved results (these results
319 are not reported here).

320 To investigate the effect of ensemble size and to determine an acceptable ensemble size for the current
321 applications, ensemble member (EM) size was increased sequentially, using the scenarios EM50, EM100,
322 EM200, EM300 and EM400 (where the suffix is the size of the ensemble), until the forecast simulations
323 appeared consistent. These scenarios were generated by resampling the downscaled ECMWF forecast
324 distributions as described above and were used to force the suite of models used. For each of the forecast
325 scenarios, the error associated with the assimilated data and the variance inflation factors were
326 “optimised” manually to provide the best results. For consistency, and in the spirit of the pseudo-real time
327 treatment of the forecast simulations, the variance inflation factors were kept consistent across all lake-
328 years considered. For each of the assimilated variables, the variance was assumed to be proportional to
329 the magnitude of the variable of interest using a percentage. Additionally, a minimum variance was
330 applied to reduce the impact of very small observed values (e.g. where epilimnetic SRP values are
331 observed to be very low or within the limit of detection) where the associated low variance would falsely
332 indicate low uncertainty.

333 **2.3.7 Assessing forecast skill**

334 Different studies have used different benchmarks to evaluate the goodness of fit of forecasts (*forecast*
335 *skill*), which are often determined by their aims. Studies tend to use either some form of “reference”
336 simulation or simulations that do not assimilate any observations (sometimes called “climatology”) which
337 serve to quantify the DA effect (e.g. Allen *et al.*, 2003 and Kim *et al.*, 2014) or solely a measure of the
338 goodness-of-fit to observations (e.g. the coefficient of determination, R_T^2). Here, as our aim was to assess
339 the value of the model for operational forecasting, we used a more stringent *persistence forecast* (e.g. see
340 Stumpf *et al.*, 2009) which uses the most recent observations as the forecast for each *forecast timestep*
341 until the next observation becomes available. In the sections below, forecast skill was assessed by
342 comparing the simulated chlorophyll *a* forecast with a persistence forecast for the entire annual
343 timeseries. The goodness of fit of the benchmark and the simulated chlorophyll *a* forecasts were
344 determined using the root-mean-square error (RMSE) as a measure. For the epilimnetic depth model, and
345 other sub-models (i.e. TF models), goodness of fit is discussed more generally by comparison with
346 observations using the coefficient of determination (R_T^2). Assessment of the forecasts of phytoplankton
347 community structure and cyanobacteria is made qualitatively as we have much lower confidence in the
348 absolute value of the observations. A discussion of how the phytoplankton species “count” data are used
349 and the associated uncertainties is provided in the relevant section below.

350 **3 Results and discussion**

351 **3.1 TF model results**

352 Transfer function models were identified for epilimnetic temperature, river temperature and river inflows
353 and outflows and all models provided good fits to the observed data during model identification: R_T^2
354 values were between 0.86 and 0.98 (Supp. Table 1). Model identification was carried out for the entire
355 period of data available (see Supp. 1) such that they were not year specific models. As detailed above, in
356 each case the models were used to forecast their respective variable deterministically.

357 **3.2 Forecasting epilimnetic depth and the phytoplankton community**

358 **3.2.1 Epilimnetic depth forecasts**

359 Epilimnetic depth forecast estimates were made for 2008-2010 for Windermere and 2008 and 2009 for
360 Esthwaite Water within the parallel EnKF scheme. Although very simplistic, the epilimnetic depth model
361 provided reasonable forecasts of epilimnetic depth when compared to those estimated from
362 observations. For both lakes, the forecasts were stable and consistent using the smallest ensemble size of
363 50 using a variance inflation factor of 1.25. Simulations for Windermere were better than for Esthwaite
364 Water (R_T^2 of 0.85 and 0.75 respectively for a 10-day-ahead forecast; Figs. 2a and 2b) and there were short
365 periods with significant deviations from the 'observed' depths in both cases. Simulation of the timing of
366 temporary stratification events at the beginning of the year was problematic for both lakes and
367 simulations tended towards overly rapid mixing during autumn turnover, particularly for Esthwaite Water.
368 Where significant deviations exist, they have the potential to reduce the forecast skill and therefore need
369 to be improved, although, importantly, epilimnetic depth estimates for much of the high cyanobacterial
370 bloom risk periods (i.e. during periods of strongest stratification) are reasonable. Given these results, the
371 epilimnetic depth estimates for Windermere appear to be adequate out to 10-days-ahead but for
372 Esthwaite they appear to be adequate for a much shorter lead time; for example, the 3-day-ahead forecast
373 is a much better fit with an improved R_T^2 of 0.81 (Fig. 2c). The adequacy of these estimates is assessed
374 more formally in association with the Chlorophyll *a* forecasts in comparison to the persistence forecast in
375 the next section.

376 **3.2.2 Chlorophyll *a* forecasts**

377 For all lake-years, multiple runs of the EM50 Forecasts gave inconsistent simulations and a higher EM size
378 was required. Forecasts for Windermere tended towards stability between the EM100 and EM200
379 scenarios (Fig. 3), which is an ensemble size consistent with previous work with relatively complex models

380 (e.g. Evensen, 1994 and Allen *et al.*, 2003). For Esthwaite Water, however, a higher ensemble size
381 appeared to be required with a size of around 400 giving consistent simulations (Fig. 4). Subsequently, in
382 the following, results presented for Windermere and Esthwaite Water are associated with the EM200 and
383 EM400 scenarios respectively. In all cases, the manually “optimised” variance inflation factor was kept
384 consistent for all lake years at a value of 1.1.

385 Although forecast simulations for Windermere appear to be relatively good visually (e.g. see Fig. 5), they
386 were not always an improvement on the persistence forecasts (Fig. 3). For 2008, the persistence forecast
387 was better than simulated forecasts for all lead times. Conversely, simulated forecasts were better than
388 the persistence forecasts for all lead times for 2009. A lead time of approximately 6 days or less was an
389 improvement on the persistence forecast for 2010 simulations.

390 For Esthwaite Water, forecast simulations were not as good as those for Windermere (Fig. 5), which is
391 consistent with previous work using PROTECH for these lakes (Page *et al.*, 2017). The forecasts for 2008
392 were, however, still better than the persistence forecast out to about 5 days ahead (Fig. 4a), but were
393 always worse than the persistence forecast for 2009 (Fig. 4b). The poorer fits for Esthwaite Water are
394 likely to be a result of the complex uncertainties associated with the timing and magnitude of SRP inputs
395 as well as the poorer simulation of epilimnetic depth reported above. In Esthwaite Water, during the
396 period where P limitation dominates phytoplankton growth, it is very difficult to represent SRP fluxes
397 appropriately, even when a representation of sediment-derived SRP fluxes was included (the addition of
398 representation of sediment-derived SRP did not improve forecasts owing to interaction between sources
399 of P: this work is not reported here). The difficulties associated with representing SRP fluxes was helped
400 to some degree by the DA, but remain problematic during times when very low concentrations were
401 present in the epilimnion; at these times, the correlations within the Kalman gain matrix would need to
402 be very well-represented to provide appropriate updates to both epilimnetic SRP concentrations and SRP

403 fluxes simultaneously. The difficulties associated with these updates are compounded by the relatively
404 low frequency of assimilation timesteps. Subsequently, even with relatively large ensemble sizes, the
405 correlations within the Kalman gain matrix have the potential to be spurious. This is not unexpected as
406 the lake system is highly dynamic and non-linear and, perhaps most importantly, the relationships
407 between the states (and parameters in some cases) are not always consistent (e.g. when the nutrient
408 states are not limiting they may have no relationship with the phytoplankton state). The temporal
409 evolution of the nutrient parameter values (modified within the DA scheme) that change SRP fluxes were
410 consistent with these uncertainties and did not show any consistent structure. Given these difficulties,
411 assimilation of higher resolution nutrient observations may be one of the most important ways of
412 improving forecasts. Conversely, for both Windermere and Esthwaite Water, forecasts were improved by
413 the modification of the background light extinction parameter, ϵ_b , within the DA scheme: its evolution
414 over the simulation periods was relatively consistent for each of the years considered (Fig. 6) and reflects
415 known simulation artefacts previously reported by Page *et al.* (2017).

416 **3.2.3 Forecasting phytoplankton community structure**

417 Forecasts of species representing the phytoplankton community structure were made without direct
418 constraint within the DA scheme. Simulations were, however, indirectly constrained by the assimilation
419 of epilimnetic depth, chlorophyll *a* and nutrients and hence are reliant on the ability of PROTECH
420 simulations to represent phytoplankton community structure where abiotic conditions for phytoplankton
421 growth are simulated adequately. They are also reliant on whether or not the phytoplankton species
422 chosen to represent the community are appropriate (Elliott, 2010, 2012; Page *et al.*, 2017).

423 Forecasts of community structure are assessed here using simulations of R- and CS- functional types.
424 These functional types were used as they dominate our study lakes. The observations to which they are
425 compared here are estimated from “counts” of algal species, which are classified into the same functional

426 groups. The “count” data were converted to biovolume using microscope measurements (Centre for
427 Ecology & Hydrology, unpublished data) and subsequently to Chlorophyll *a* using the relationships in
428 Reynolds (1984). This chain of approximations means that the observed data are associated with
429 significant uncertainty. Accordingly, we used the relative abundance of each functional type for each
430 observation timestep to partition the observed chlorophyll *a* concentration as our final estimate and
431 estimated the sampling/analytical error to be +/- 25% and the overall error to be +/- 50% in accordance
432 with Page *et al.* (2017).

433 A comparison of the uncertain observations of R- and CS- functional types are presented in Fig. 7 where
434 it can be seen that for most lake-years the overall pattern of the simulations are consistent with the
435 observations. There are some periods where the simulations are not consistent, which are associated
436 primarily with the period of transition between the early blooms of R-type species and succession by CS-
437 types (approximately between days 100 and 200). This inconsistency can clearly be seen for Windemere
438 2008 and 2009 (Figs 7a and 7d) and is most likely associated with inadequate representation of nutrient
439 fluxes and subsequent periods of nutrient limitation (Page *et al.*, 2017). There are also some periods
440 where the overly rapid mixing simulated by the epilimnetic depth model made it difficult to simulate the
441 relatively high observed biomass: this is particularly evident for CS-species in Esthwaite Water 2008 (Fig.
442 7k) and R-species in Esthwaite Water 2009 (Fig. 7l); these inconsistencies are a direct result of the spurious
443 deep mixing events simulated around days 220 and 250 for 2008 and 2009 respectively (see Fig. 2 b and
444 c) and strengthen the requirement to improve the epilimnetic depth model.

445 **3.2.4 Forecasting cyanobacteria**

446 Observations of Cyanobacteria are estimated in the same way as functional species types discussed in the
447 previous section and are associated with similar uncertainty (see Fig. 7). As PROTECH simulates the
448 functional algal community using the dynamics of a number of selected individual species, the philosophy

449 behind this method means that the forecasts of individual species are not as robust as those for functional
450 community structure and are hence more uncertain. This is the case for forecasts of cyanobacteria where
451 they are represented by more than one functional type: e.g. for Windermere cyanobacteria are
452 represented by *Planktothrix*, an R-type species, together with *Aphanizomenon flos-aquae* and
453 *Dolichospermum* which are CS-type species (see Table Supp. 2). In this situation, the interchangeability of
454 species with similar functional behaviour, but which have differing species traits, requires additional
455 interpretation for forecasts of cyanobacteria to be made. For example, the simulations of the R-species
456 *Planktothrix* for all lake-years for Windermere result in overestimations of cyanobacteria concentrations
457 for the periods where *Planktothrix* proliferates (approximately between days 150 and 275: Figs 7c, 7f &
458 7i). Cyanobacteria forecasts, made for this study, are also a spatial average for each lake, constrained
459 using data collected at one point; they therefore do not necessarily correspond with the risk from near-
460 surface accumulations of cyanobacteria where significant spatial heterogeneity exists, as can be the case
461 for wind-blown cyanobacterial species (e.g. George and Heaney, 1978). Extending point forecasts to
462 spatial forecasts for species that have these characteristics is hence an additional challenge. However,
463 forecasts may be presented as probabilistic or possibilistic risk estimates, such as the likelihood of a
464 cyanobacterial concentration of greater than a given critical threshold: this will be the focus of further
465 research.

466 **4 Conclusions**

467 We rigorously tested the ability of the phytoplankton community model PROTECH to make forecasts of
468 phytoplankton community structure within a data assimilation scheme using the Ensemble Kalman Filter.
469 Some forecasting success was shown for chlorophyll *a*, but not all forecasts were better than a persistence
470 forecast. The results typically indicated a reduction in chlorophyll *a* forecast skill with length of forecasting
471 period with forecasts for up to four or five days showing greater promise than those for longer time-

472 scales. Associated forecasts of phytoplankton community composition, represented by functional algal
473 types, were broadly consistent with observations. Translation of forecasts of functional algal types to
474 forecasts of cyanobacteria are challenging because of functional similarities between species which may
475 or may not be cyanobacteria. Improvements in forecasts are likely to come from higher frequency
476 observations for both chlorophyll *a* and nutrient concentrations. Fluorescence-based field sensors for
477 both chlorophyll and the cyanobacterial pigment phycocyanin exist and while they are not completely
478 quantitative, they would permit patterns of change to be captured. While higher frequency observations
479 for these variables should help improve forecasts, they will also simultaneously improve the persistence
480 forecast. It, therefore, remains to be seen whether or not a modelled forecast driven with improved
481 observations would provide a significant improvement over the associated persistence forecast and the
482 potential to forecast algal blooms in this type of lake.

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619 **Supplementary information**

620 **Supp. 1 Transfer Function models for forecasted inputs**

621 The epilimnetic depth model requires forecasts of epilimnetic temperature, river in/outflows and river
622 temperature. Each TF model that provides these forecasts was identified (as outlined above) using the
623 available timeseries data. The epilimnetic temperature (T_e) at day t is given by:

624
$$T_{e(t)} = -a \cdot T_{e(t-1)} + b1 \cdot T_{a(t)} + b2 \cdot R_{sw(t)} + b3 \cdot \frac{1}{D_{e(t-1)}} + b4 \cdot (W_{s(t-1)})^3$$

625 Where, T_a is the air temperature, R_{sw} is SW radiation, D_e is epilimnetic depth and W_s is the wind speed.
626 The model coefficients are denoted a , $b1$, $b2$ and $b3$ (see Table Supp. 1 for values). One model for each
627 lake was identified from the available data (2008 to 2010 for Windermere and 2004 to 2009 for Esthwaite
628 Water).

629 The lake in/outflow TF model was identified as a 1st order model with a nonlinear rainfall filter (see Young
630 and Beven, 1994) and took the form:

631

632
$$Q_{r(t)} = -a \cdot Q_{r(t-1)} + b \cdot P_{(t)} \cdot Q_{r(t-1)}^\beta$$

633

634 where Q_r is the river in/outflow, P is precipitation and a , $b1$ are TF model coefficients where β is the
635 nonlinear rainfall filter parameter. The model for Windermere was identified using Rainfall data from
636 Ambleside and flow data from the Environment agency Gauge at Newby Bridge for the years 2008 to 2010
637 (National River Flow Archive: <http://www.ceh.ac.uk/data/nrfa/>).

638 River temperature (T_Q) was estimated using observed data from Troutbeck (Windermere) for the years
639 1997 to 2006:

640
$$T_{Q(t)} = -a \cdot T_{Q(t-1)} + b \cdot T_{a(t)}$$

641 **References (supplementary information)**

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644

645 **Table 1 Study Lakes and primary characteristics[§]**

Name/location	Mean Depth (m)	Max. Depth (m)	Max. Length (m)	Volume (m ³)	Catchment Area (km ²)	Residence Time (days)
Windermere (South Basin)	16.8	41	9300	1.06 x 10 ⁸	230.5	100
Esthwaite Water	6.4	15.5	2500	5.97 x 10 ⁶	17.1	100

646 [§] Details from Ramsbottom (1976)

647

648 **Table 2 Forcing inputs and downscaling relationships**

Model Inputs	Downscaling factor/relationship	Uncertainty sampled
Air Temp (T_a ; K)	Windermere: $0.095(T_a^{\S}) + 279.75^{**}$ Esthwaite Water: $0.013(T_a^{\S}) + 280.16^{**}$	Y (Regression)
Solar Radiation (SR; Wm ⁻²)	0.85	N
Wind Speed (W; m s ⁻¹)	0.38 [*]	Y (Gamma Dist.)
Relative Humidity (RH; %)	1	N
Cloud Cover (Cc; eighths)	1.25	N
Rainfall (R; mm)	3	N
Nutrient Inputs (P; N; SiO ₂ / mg m ⁻³)	See section 2.2.3	Y (Gamma Dist.)

649 T_a^{\S} is the forecast air temperature (K); ** see Section 2.2.2 for additional lake-effect correction; * see Section 2.2.2 for additional
650 wind direction correction.

651

652 **Table 3 Observed data assimilated in the EnKF scheme**

Assimilated state	Frequency	Source
Epilimnetic Temperature (°C)	Daily	buoy obs.
Hypolimnetic Temperature (°C)	Daily	buoy obs.
Epilimnetic depth (m)	Daily	buoy obs.
Chlorophyll a (mg m ⁻³)	≈14 days	Monitoring
Nutrient Inputs (SRP; N; SiO ₂ / mg m ⁻³)	≈14 days	Monitoring

653

654

655

656

657 **Table 4. States and parameters included in the ENKF scheme**
 658

State/Parameter	Acceptable range	Observational error (%)	Initial distributions (uniform)**
Epilimnetic Temp. (T_e , °C)	2-25	5	5.5-7 (W); 4-6(E)
Hypolimnetic temp. (T_h , °C)	2-25	10	5.5-7 (W); 4-6(E)
Epilimnetic depth (D_e , m)	0.5-max. depth	5	41 (W); 15.5(E)
Chlorophyll <i>a</i> (mg m^{-3})	1e^{-6} - 1e^3	10	3-4.5 (W); -4.5-6 (E)
Background light extinction (ϵ_{br} , m^{-1})	0.15-0.9	N/A	0.15-0.6(W); 0.45-0.75(E)
Epilimnetic P conc. (P_e , mg m^{-3})	1e^{-6} - 1e^4	25	10-20(W); 8-15(E)
Epilimnetic DIN conc. (N_e , mg m^{-3})	1e^{-6} - 1e^4	25	400-700(W); 500-1100(E)
Epilimnetic SiO ₂ conc. (Si_e , mg m^{-3})	1e^{-6} - 1e^4	25	1500-2500(W); 2000-2500(E)
Diffuse P input multiplier (P_f , dimensionless)	0.05-7	N/A	0.01-1.5
Diffuse DIN input multiplier (N_f , dimensionless)	0.1-3	N/A	0.5-1.2
Diffuse SiO ₂ input multiplier (Si_f , dimensionless)	0.1-3	N/A	0.5-1.2
Point source P input multiplier ($WwTW_f$, dimensionless)	0.01-2	N/A	0.1-1.4

659 ** Where distributions are different for each lake W = Windermere; E = Esthwaite Water

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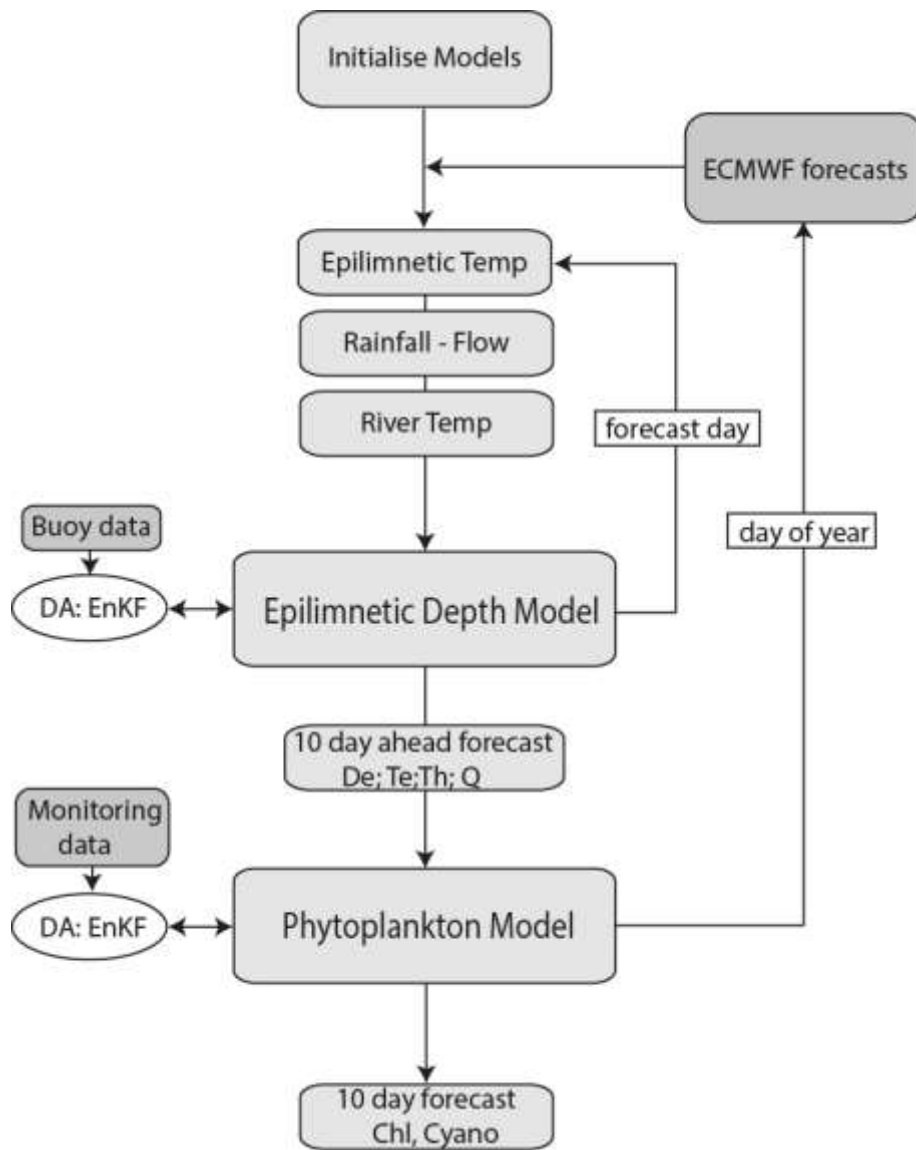


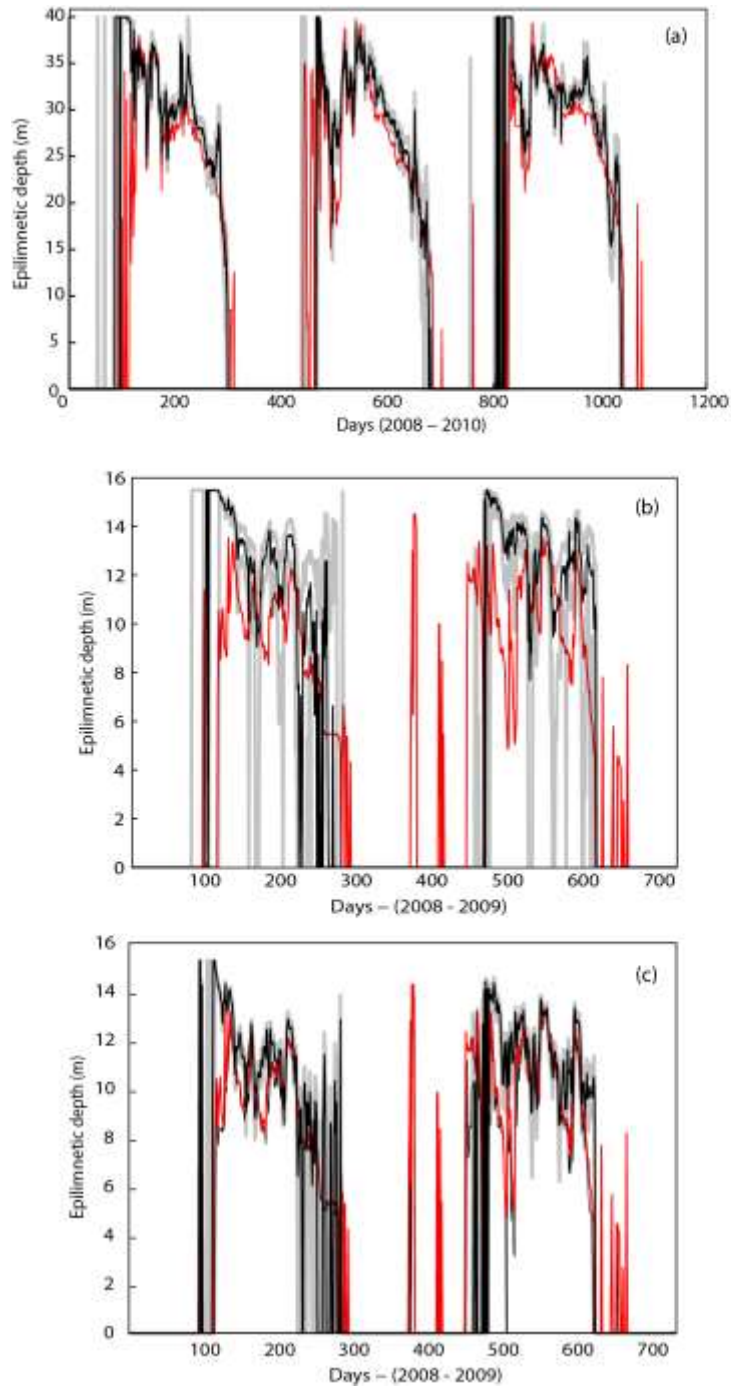
Figure 1. Schematic

662

663 diagram of the forecasting system. The schematic shows sequential model input-output structure and
 664 DA strategy. De is epilimnetic depth; Te is epilimnetic temperature; Th is hypolimnetic temperature, Q is
 665 lake inflow/outflow and Chl and Cyano are the concentration of total phytoplankton chlorophyll a and
 666 cyanobacterial chlorophyll a respectively.

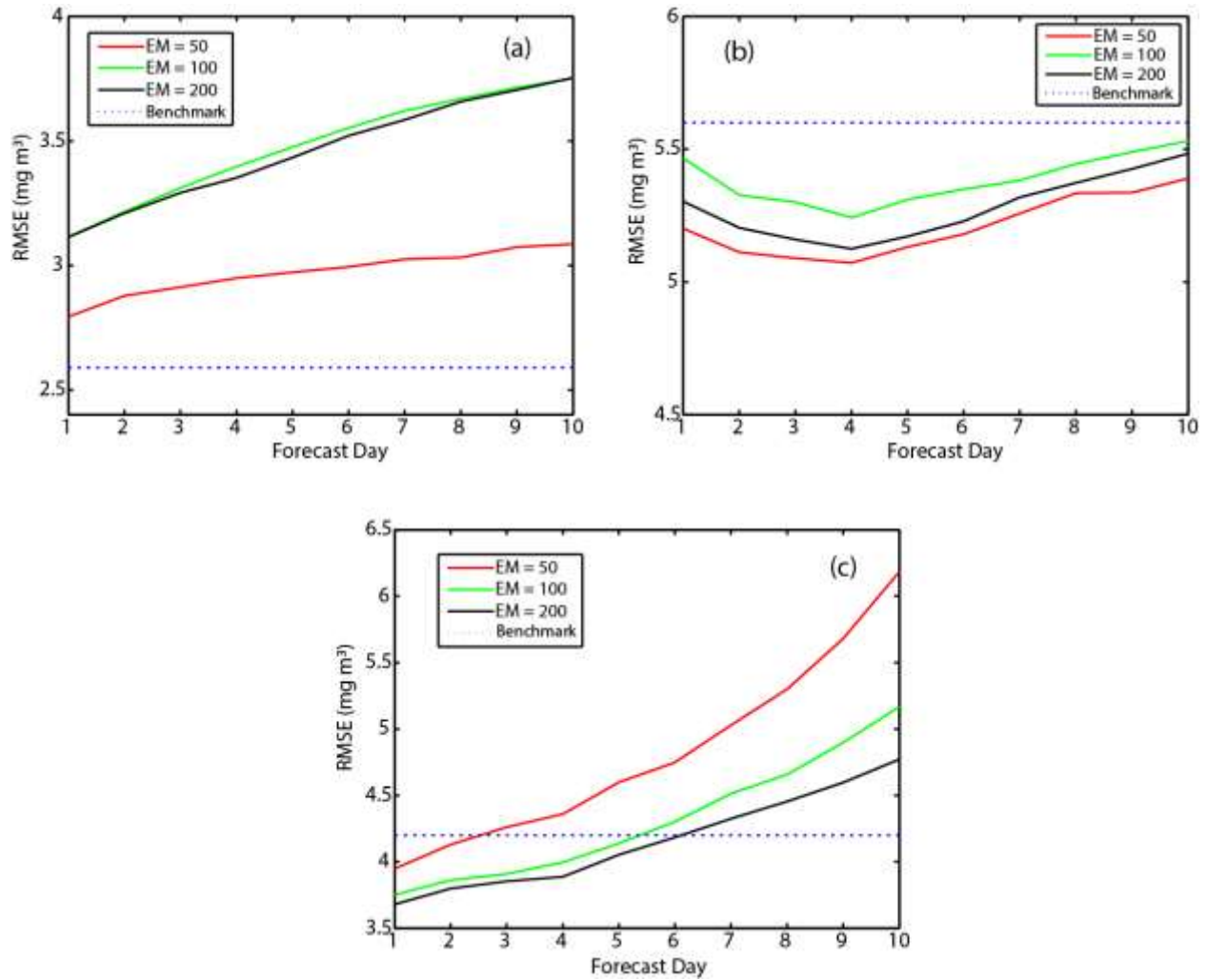
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669

670 Figure 2. Simulated and measured epilimnetic depth. Results shown for (a) Windermere 2008-2010 10-
 671 day-ahead, (b) Esthwaite Water 2008 and 2009 10-day-ahead and (c) Esthwaite Water 2008 and 2009 3-
 672 day-ahead: “observed” epilimnetic depth (red line), 50th percentile of the ensemble of simulated
 673 epilimnetic depth (black line) and 5th and 95th percentiles (grey lines).



674

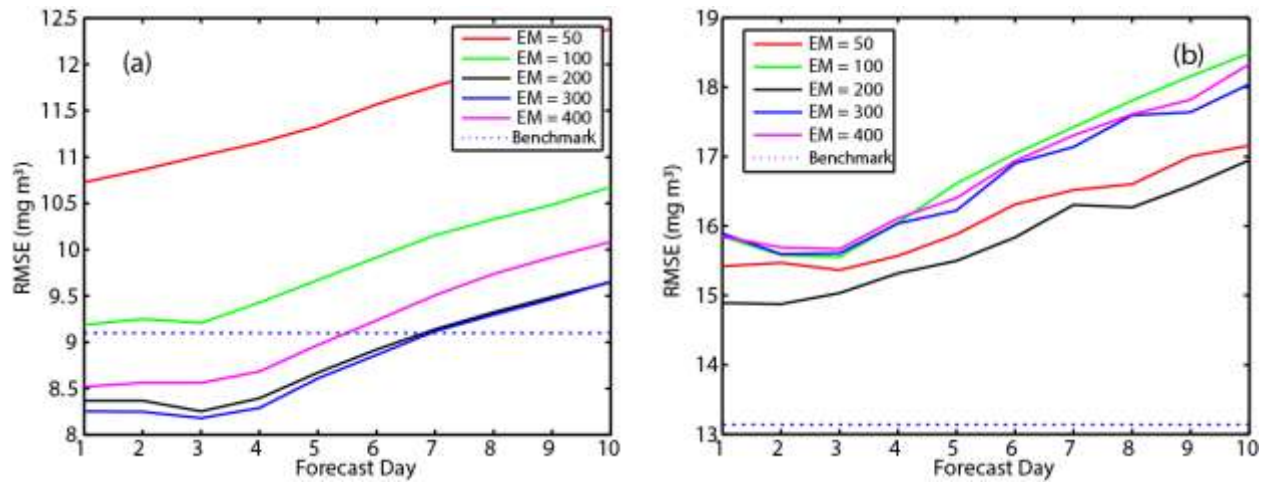
675 Figure 3. Chlorophyll a forecast skill for the differing ensemble size scenarios. Results are shown for (a)

676 Windermere 2008, (b) Windermere 2009 and (c) Windermere 2010, compared to the benchmark

677 persistence forecast. Note that lower ensemble sizes can give “randomly” better forecast performance

678 (e.g. EM = 50 in pane (a))

679

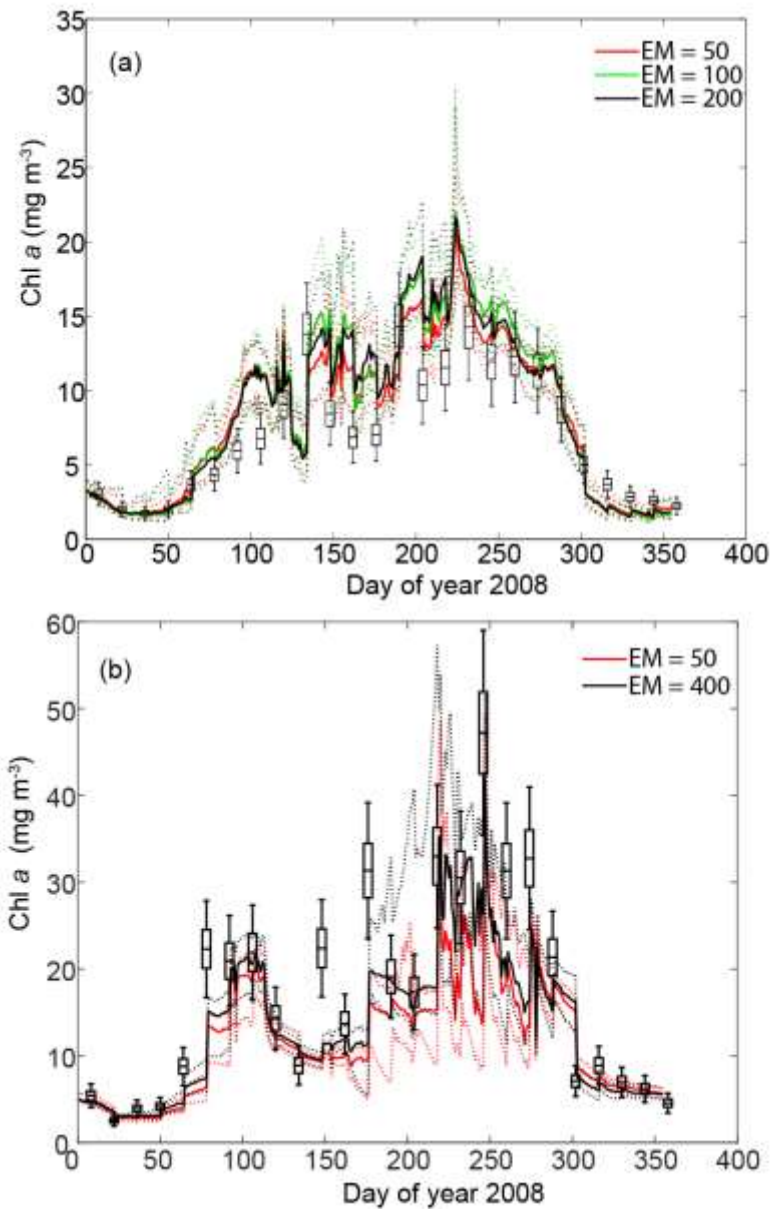


680

681 Figure 4. Chlorophyll a forecast skill for the differing ensemble size scenarios. Results are shown for (a)

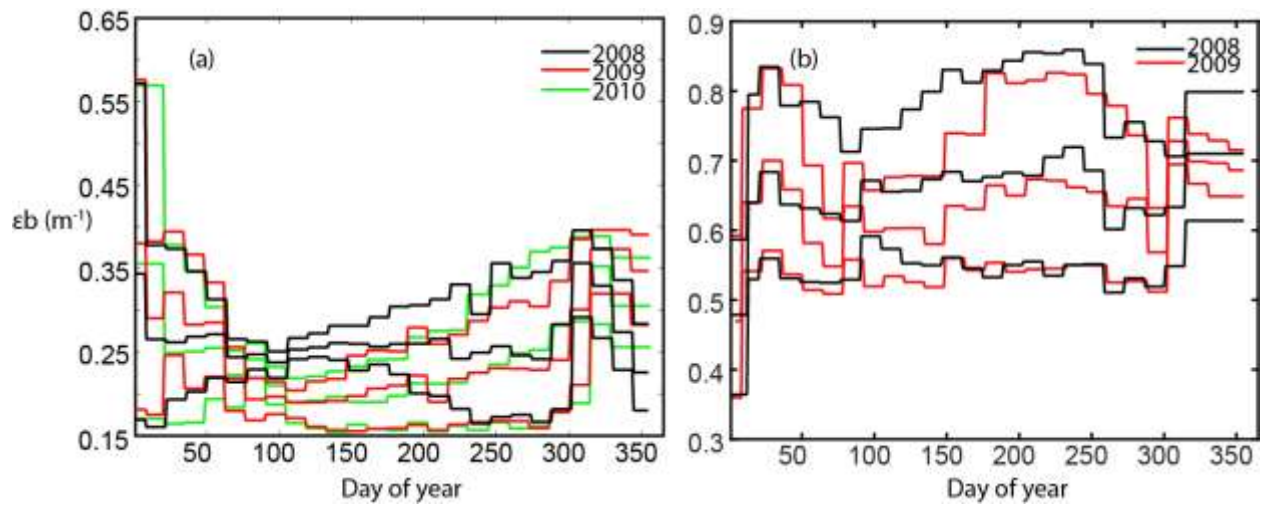
682 Esthwaite Water 2008 and (b) Esthwaite Water 2009, compared to the benchmark persistence forecast.

683



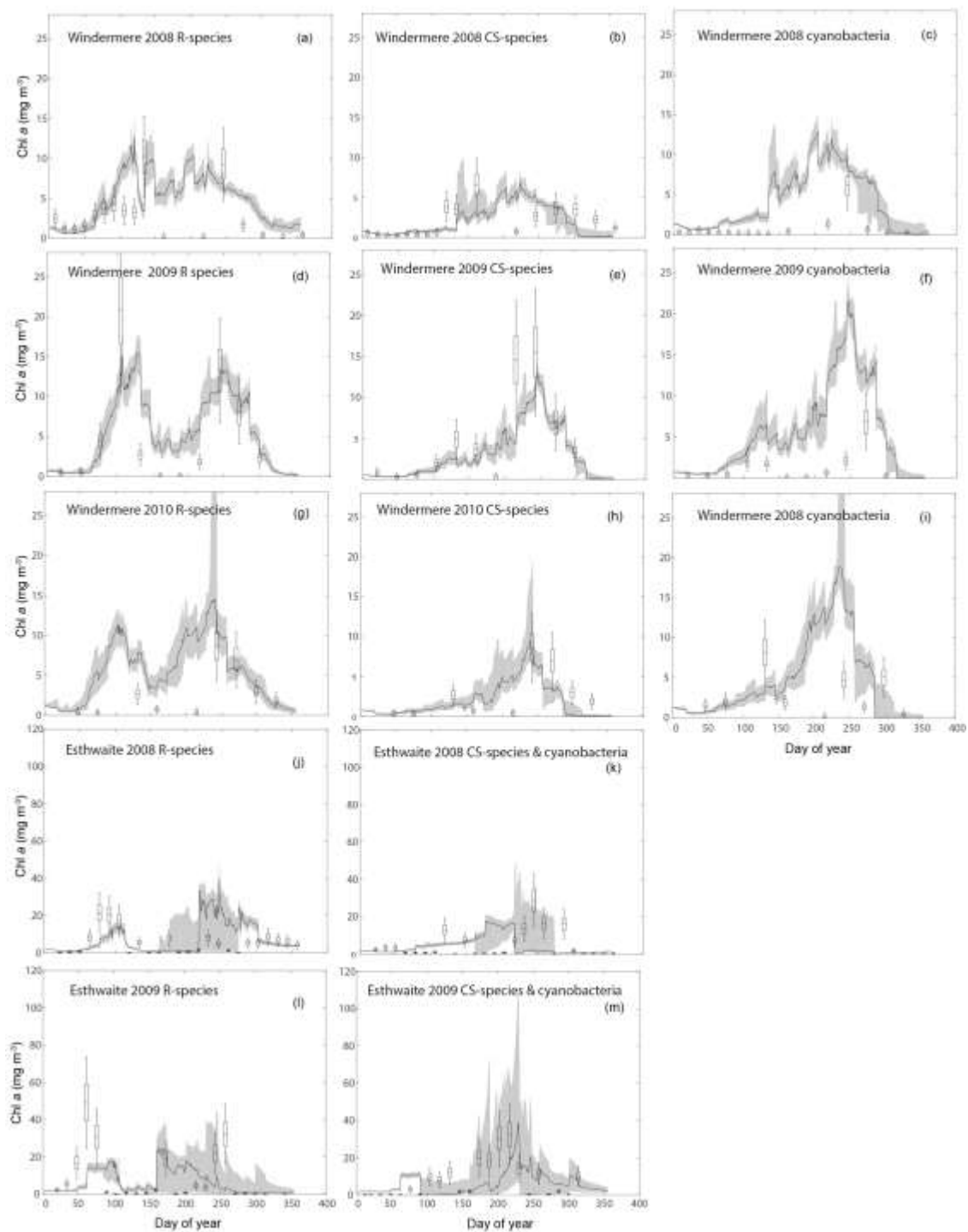
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685 Figure 5. Measured and forecast phytoplankton chlorophyll a in the two lakes during 2008. Results
 686 show concatenated forecasts for: (a) 10-day-ahead for Windermere 2008 for ensemble member sizes
 687 (EM) of 50, 100 and 200; (b) 5-day-ahead for Esthwaite Water 2008 for ensemble member sizes (EM) of
 688 50 and 400. Solid lines are 50th percentile of ensemble and dotted lines are 5th and 95th percentiles.
 689 The box and whisker symbols represent the analytical uncertainty and the total uncertainty of +/- 8%
 690 and +/- 25% (see Page et al, 2017).



691

692 Figure 6. The evolution of the background light extinction coefficient parameter (ϵ_b). Results are shown
 693 for (a) Windermere 2008, 2009 and 2010 and (b) Esthwaite Water 2008 and 2009. The three lines in
 694 each colour are the 5th, 50th and 95th percentiles of the EM200 (Windermere) and EM400 (Esthwaite
 695 Water) ensembles.



696

697 Figure 7. Concatenated five-day ahead forecasts of R-species, CS-species and cyanobacteria
 698 concentration for all lake years; black line is 50th percentile and grey shaded area represents the 5th
 699 and 95th percentiles of the ensemble: EM200 and EM400 for Windermere and Esthwaite respectively.

700 The box and whisker symbols represent the analytical uncertainty and the total uncertainty estimated
 701 by the project team. Note that 5-day ahead forecasts are presented as approximately this lead time
 702 provided the most consistently acceptable results.

703

704

705 **Table Supp. 1 Transfer Function parameters and goodness of fit (W = Windermere; E = Esthwaite Water)**

		a		b1 (β)		b2		b3		b4		τ		R_T^2	
		W	E	W	E	W	E	W	E	W	E	W	E	W	E
Lake Surface Temperature (T_s)		-0.9449	-0.899	0.055	0.093	0.0008	0.0025	0.0011	0.0022	-0.0007	-0.0012	[0,0,0,0]	[0,1,1,0]	0.97	0.98
River in/outflow (Q_r)		-0.7717	-0.829	11.141 (0.2)	0.022 (0.3)			-	-			1	0	0.92	0.86
River Temperature (T_a)		-0.900	-0.900	0.1005	0.1005	-	-	-	-	-	-	0	0	0.87	0.87

706

707 **Table Supp. 2. Species used to represent algal communities. Functional algal types and an indication of**
 708 **classification as cyanobacteria given are in parenthesis: functional types follow Reynolds (1988).**

Windermere	Esthwaite Water
<i>Aphanizomenon flos-aquae</i> (CS; Cyano)	<i>Asterionella</i> (R)
<i>Aulacoseira</i> (R)	<i>Aulacoseira</i> - 2008 (R); <i>Fragilaria crotonensis</i> -(2009 (R)
<i>Asterionella</i> (R)	<i>Aphanizomenon flos-aquae</i> (CS; Cyano)
<i>Cryptomonas</i> (CSR)	<i>Aphanothece clathrata</i> (CS; Cyano)
<i>Dolichospermum</i> (CS; Cyano)	<i>Cryptomonas</i> (CSR)
<i>Monoraphidium</i> (CS)	<i>Dictyosphaerium pulchellum</i> (R)
<i>Paulschulzia tenera</i> (S)	<i>Dolichospermum</i> (CS; Cyano)
<i>Planktothrix</i> (R; Cyano)	<i>Eudorina</i> (S)

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