

1 Assessing multiple stressor effects to inform climate 2 change management responses in three European 3 catchments

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33 **Abstract**

34 Interactions between stressors, including climate change and nutrient enrichment, are
35 expected to be wide spread in firewater ecosystems, although the extent to which
36 these effects are locally moderated is not well understood. Our understanding of the
37 forms and frequency of occurrence of such interactions is limited; assessments using
38 field data have been constrained as a result of varying data forms and quality. To
39 address this, we demonstrate a statistical approach capable of assessing multiple
40 stressor interactions using contrasting data forms in three European catchments (Loch
41 Leven Catchment, UK: assessment of phytoplankton response in a single lake with
42 time series data, Pinios Catchment, Greece: macroinvertebrate response across
43 multiple rivers using spatio-temporal data; and Lepsämäenjoki Catchment, Finland:
44 phytoplankton response across multiple rivers using spatio-temporal data). Statistical
45 models were developed to predict the relative and interaction effects of climate change
46 and nutrient enrichment sensitive indicators (stressors) on indicators of ecological
47 quality (ecological responses), within the framework of linear mixed effects models
48 (LMEs). In all catchments, indicators of nutrient enrichment were identified as the
49 primary stressor with climate change sensitive indicators causing secondary effects
50 (Loch Leven: additive, total phosphorus x precipitation; Pinios: additive, nitrate x
51 dissolved oxygen; Lepsämäenjoki: synergistic, TP x summer water temperature), the
52 intensity of which varied between catchments and along the nutrient stressor gradient.
53 Simple, stressor change scenarios were constructed for each catchment and used, in
54 combination with mechanistic evidence support the models, to explore potential
55 management responses.

56

57 **1. Introduction**

58 Fresh waters provide vital services to society including the provision of clean drinking
59 water, recreation and tourism, pollutant processing, biodiversity, food provision, and
60 energy (Reynard and Lanzanova, 2017). These services generally rely on good water
61 quality, underpinned by stable ecological processes, which are threatened globally by
62 multiple and potentially interacting stressors (Dodds et al., 2013), including nutrients,
63 hydrological modification, toxic chemicals, and non-native invasive species (Birk et al.,
64 2019). Amongst these, climate change and nutrient stressors are expected to act
65 across large scales, although it has been proposed that management of nutrients may
66 be achievable at local scales to relieve effects of both in fresh water ecosystems (Moss
67 et al., 2010).

68 It is clear that some stressors (e.g. nutrient enrichment) can be more easily
69 manipulated at the local scale than others (Friberg et al., 2016). For example,
70 catchment or ecosystem scale nutrient reduction has been demonstrated as an
71 effective approach in lake restoration (Jeppesen et al., 2005; Spears et al., 2016). In
72 contrast, other stressors acting on ecosystems but manifested from large-scale
73 drivers, such as climate change, may be impossible for catchment managers to
74 control. Stressors driven by anthropogenic activities operating at different scales can
75 also interact, for example, changes in temperature and flushing rate can alter
76 ecological responses to nutrient loading in rivers (Bowes et al., 2016) and lakes
77 (Carvalho et al., 2012). In fact, it is widely acknowledged that many mechanisms exist
78 through which the effects of climate change may be moderated in lakes and rivers
79 including geographically distinct projections in weather patterns, in the influence of
80 ecosystem morphology, and in the influence of other stressors, including nutrient
81 enrichment (Adrian et al., 2009). As a result, some authors have suggested that

82 disentangling these effects may be 'challenging, if not infeasible' (Benateau et al.,
83 2019).

84 Weyhenmeyer et al. (2007) provide empirical evidence on increasing rates of nitrate
85 depletion in European shallow lakes, suggesting that this phenomenon is driven by a
86 combination of decreased catchment and atmospheric nitrate loading as well as
87 increased denitrification related to warming between 1988 and 2003. Further, Moss et
88 al. (2011) propose that such interactions will be wide spread, with local modifications
89 (e.g. in intensity of nutrient stress), resulting, generally, in exacerbation of
90 eutrophication effects including more severe and frequent algal blooms. It is, therefore,
91 important that such interactions be confirmed at a relevant scale of interest to support
92 the development of novel multiple-stressor management strategies.

93 We currently lack robust statistical frameworks to detect and predict the effects of
94 multiple stressor mitigation options at catchment scales. Such a framework would
95 enable comparisons of frequency of occurrence and interaction forms across
96 ecosystems, scales, and data types (e.g. experimental, spatial, temporal,
97 spatiotemporal) common across routine monitoring programmes. Such a framework
98 would enable comparisons of frequency of occurrence and interaction forms across
99 ecosystems, scales, and data types (e.g. experimental, spatial, temporal,
100 spatiotemporal) common across routine monitoring programmes. One important
101 consideration is that data forms and frequency vary significantly between ecosystems.
102 Feld et al. (2016) presented a synthesis of approaches for determining the presence
103 of interactions between multiple stressors in freshwater ecosystems in this context,
104 including the use of generalised linear mixed effects modelling (GLMM) and Birk et al.
105 (2020) demonstrate that this approach is applicable to all forms of data to identify
106 interaction forms (Table 1) across scales in fresh waters. Here we extend this

107 approach to assess the probability of exceedance of water quality stressors when
108 applied to future stressor change scenarios (e.g. Figure 1). This approach addresses
109 two important statistical conditions necessary to underpin practical guidance to water
110 managers: (1) that models should be constructed to determine interactions,
111 specifically, and (2) that a standardized approach for model construction (i.e. stressor
112 selection) is necessary. These conditions minimize bias in the model construct to
113 improve representativeness and deliver the best 'model fit', statistically, whilst
114 acknowledging the importance of scale and data quality as limiting factors in their
115 application.

116 We demonstrate this approach for three contrasting (i.e. data forms, frequency, and
117 scale) European catchments to test the hypothesis that significant interaction effects
118 would be detectable between nutrient and climate sensitive stressors on ecological
119 quality indicators, known locally to be sensitive to nutrients. The catchments were
120 selected to represent contrasting but realistic data forms: Loch Leven Catchment, UK:
121 assessment of phytoplankton responses in a single lake with time series data; Pinios
122 Catchment, Greece: macroinvertebrate community response across multiple rivers
123 using spatial data; and Lepsämäenjoki Catchment, Finland: phytoplankton response
124 across multiple rivers using spatio-temporal data. The resultant best fit paired stressor
125 GLMMs were applied to estimate the expected mean effect of stressor change on
126 ecological indicators relative to critical values. We discuss the strength of the
127 mechanistic evidence to support the model outputs and the implications of the
128 analyses with respect to informing local scale multiple stressor management
129 responses.

130

131 **2. Methods**

132 Our approach was to utilise local mechanistic understanding to select indicators
133 sensitive to climate change and nutrient enrichment as well as ecological quality
134 indicators being utilised to inform environmental management at the local scale. As
135 such, we do not produce comparable or balanced data sets with which to compare
136 statistically the model outputs between catchments and we acknowledge that other
137 stressors may produce higher order interactions not captured here. We acknowledge
138 that data availability on such indicators will vary between sites and across scales (Birk
139 et al., 2020) and also that their biophysical behaviour will be moderated depending on
140 the ecosystem morphology and geographical locations (Adrian et al., 2009). As such,
141 the model outputs do not offer general explanation of wider scale ecological
142 responses. For each catchment, we used a 'dredge' analysis to produce a range of
143 models including combinations of pairwise stressor effects against ecological quality
144 indicators, the latter calculated as per requirements of site specific ecological quality
145 assessment procedures. From this analysis, we selected the best fit models using
146 model Akaike Information Criterion (AIC) values to explore catchment specific future
147 stressor change scenarios, informed by local climate change projections. The
148 indicators included from each site and the model selection criteria are described in
149 detail in the following sections.

150 **2.1 Study site description, data sources, and stressor change scenarios**

151 **2.1.1 Loch Leven**

152 Loch Leven, a shallow lake in the UK, offers a time series from a single sample site
153 with roughly fortnightly sampling frequency between 1967 and 2017. Data were
154 obtained from the Loch Leven long term monitoring dataset (May & Spears, 2012)
155 across multiple years (1968-2013) with 39 years of data used in the final analysis as

156 a result of missing values. In this study we consider the ecological response as
157 chlorophyll *a* concentration in the water column, a proxy for phytoplankton
158 concentration, as well as potential stressor indicators for nutrient enrichment (i.e. total
159 phosphorus (TP) concentrations) and climate change (i.e. water temperature and
160 precipitation) (Table 2). Water temperature, chlorophyll *a*, TP concentrations were
161 determined roughly fortnightly during the monitoring period and processed to provide
162 mean values as indicated in Table 2. Stressor data were averaged across growing
163 season (May through September) and autumn/winter (October through April) with
164 chlorophyll *a* averaged annually to be more in line with WFD methodology (Poikane et
165 al., 2010). Methods for the determination of the Loch Leven indicators are described
166 by Dudley et al. (2013), with the exception of precipitation data which were retrieved
167 from the British Atmospheric Data Centre and processed from daily values
168 representing local conditions as described by Carvalho et al. (2012). These indicators
169 have been shown previously to play an important role in ecological community
170 structure in Loch Leven (Ferguson et al., 2007).

171 Target values for chlorophyll *a* concentration ‘good-moderate’ boundary were selected
172 from the site-specific targets defined by the EU Water Framework Directive (WFD) for
173 annual mean concentrations at $11 \mu\text{g L}^{-1}$ (Carvalho et al., 2009). A review of target
174 setting for Loch Leven and as conducted by the WFD generally is offered by Carvalho
175 et al. (2012) and Hering et al. (2010), respectively.

176 As a result of climate change, by 2050 the east of Scotland is expected to experience
177 a 1-2°C rise in annual and summer average daily temperature, at the 10% probability
178 level and assuming a medium emissions scenario (UKCP09 SRES A1B;
179 Nakićenović et al., 2000). Under the same scenario, summer and winter precipitation
180 is predicted to decrease by 20-30% and increase by 0-10%, respectively. More

181 frequent and intense rainfall events are also predicted. O'Reilly et al. (2015) report an
182 observed warming rate of about 0.7°C per decade in Loch Leven surface waters.

183 **Pinios Catchment, Greece**

184 The Pinios Catchment represents multiple river monitoring data across 76 river
185 monitoring sites collected during autumn (i.e. between September, October,
186 November) 2002. The ecological response indicator used was Average Score Per
187 Taxon (ASPT) calculated using macroinvertebrate taxon data from each site (Armitage
188 et al., 1983). Climate change sensitive indicators included water temperature,
189 discharge and dissolved oxygen concentration and indicators of nutrient enrichment
190 included PO₄-P and NO₃-N concentrations. Other authors have confirmed the
191 sensitivity of dissolved oxygen to climate change in fresh waters (Adrian et al., 2009;
192 Benateau et al., 2019) where hypoxic events have been confirmed to coincide with
193 droughts and low-flow conditions in the Pinios catchment. Target values for ASPT
194 scores were set according to Lazaridou et al. (2016) and represent the 'good–
195 moderate' boundary as defined by the EU WFD at 4.81. A description of the methods
196 used for these determinands in the Pinios Catchment are available from Panagopoulos
197 et al. (2014).

198 Climate change projections according to the most pessimistic scenario (RCP 8.5 rising
199 emissions) predict an approximately 2 °C rise in mean annual air temperature and a
200 10% decrease in annual precipitation for the Pinios catchment by 2060 (Stefanidis et
201 al., 2018). Assuming that projected increases in surface water temperatures are often
202 50 % to 70 % of the projected increases in air temperature (EEA, 2008), a 2 °C rise in
203 mean annual air temperature could mean a 1.4 °C rise in water temperature. We

204 assume here that these changes will result in a decrease in dissolved oxygen
205 concentration as discussed in detail by Stefanidis et al. (2018).

206 **2.1.2 Lepsämäenjoki Catchment, Finland**

207 The Lepsämäenjoki Catchment (214 km²) is a sub-basin of the Vantaanjoki River Basin
208 in Southern Finland. It belongs to the Long-Term Ecosystem Research Network
209 ([http://www.lter-europe.net/lter-europe/about/organisation/facility-types/lter-](http://www.lter-europe.net/lter-europe/about/organisation/facility-types/lter-platforms)
210 [platforms](http://www.lter-europe.net/lter-europe/about/organisation/facility-types/lter-platforms)) and is one of the best studied catchments in the drainage basins of the Gulf
211 of Finland and the Archipelago Sea in the Baltic Sea. In contrast to other large
212 catchments, these drainage basins consist of several small river catchments draining
213 directly to the sea. Thus, the data set for the Lepsämäenjoki Catchment was
214 supplemented by measurements from the neighbouring catchments with similar soil
215 and agricultural production types. The resulting data set represents 10 river sample
216 sites which were sampled 7 to 25 times a year during the period 1985-2014. The
217 ecological response indicator chosen for this catchment was summer mean
218 chlorophyll *a* concentration. Climate change sensitive indicators included estimates of
219 modelled catchment run-off and water temperature and nutrient enrichment indicators
220 included TP concentration. The methods used for each of these determinands are
221 described by Niemi et al. (2001). The target for summer mean chlorophyll *a*
222 concentration was set at 14.5 µg L⁻¹ using expert judgement.

223 The mean annual precipitation in the area is 650 mm, and the mean annual
224 temperature is +4°C. In winter, temperature drops below 0°C. Climate change
225 projections, according to the most pessimistic scenario (RCP 8.5 rising emissions),
226 predict an increase of approximately 2.5 °C in mean annual air temperature and less

227 than 10% increase in annual precipitation by 2060. The increase is most highlighted
228 in spring and autumn.

229 **2.2 Data processing and model construction**

230 **2.2.1 Two-way interaction models**

231 For each dataset (Table 2), statistical models were developed to predict the ecological
232 quality indicators as a function of two main stressor effects and their interaction, within
233 the framework of linear mixed effects models (LMEs). All response variables were
234 modelled with Gaussian errors. The exact form of the model fixed and random effects
235 varied depending on the dataset structure as described below. However, the full LME
236 specification was,

$$237 \quad y = b_0 + b_1x_1 + b_2x_2 + b_3x_1x_2 + S + Y + \epsilon$$

238 in which y is the response variable, x_1 and x_2 are two stressor covariates, the b terms
239 are the model fixed effect coefficients and ϵ is the residual error. For the multi-site and
240 multi-year study at Lepsämäenjoki, it was necessary to include normally distributed
241 random effects for site S (to account for repeated measures at the same site) and year
242 Y (to account for repeated measures over time). For simplicity, we only included these
243 random effects as random intercepts and not slopes. However, our approach could be
244 extended to specific applications where sufficient data can accommodate more
245 complex mixed effects models. No random effects were needed for the purely
246 temporal (Leven) or spatial (Pinios) studies. As such S and Y were dropped from their
247 model specification, simplifying the model to a standard linear model (LM).

248 All models were fitted in R by maximum likelihood using the stats or lmerTest packages
249 (Kuznetsova et al., 2017) for LM and LME models, respectively (R Core Team, 2020).

250 Prior to model fitting the response variables and covariates were transformed to

251 normal distributions using Box-Cox transformations, offset by a small value to ensure
252 all values of the variable were greater than 0. This ensured the models met
253 assumptions of normality of residuals, checked by examining model residual plots.

254 For each dataset, a set of candidate stressor variables was identified as described
255 above (Table 2). To identify the best combinations of stressor variables to use we
256 conducted a ‘dredge’ analysis in which all possible model combinations with up to two
257 main fixed effects and their interaction were fitted. For simplicity we did not consider
258 models with more fixed effects, though the analysis described below can
259 straightforwardly accommodate more complex models. Random effects were not
260 varied in model selection, as we considered them imposed by the data structure. For
261 the purposes of the analysis described below, the most parsimonious model was
262 selected for each catchment based on the lowest Akaike Information Criteria (AIC_c);
263 although the output of the dredge analyses is provided displaying all model
264 combinations returned. We opted not to utilize model averaging approaches as they
265 may obscure the detection of interactions.

266 **2.2.2 Risk of threshold exceedance**

267 The probability of the response variables exceeding the site-specific threshold values
268 were evaluated across both stressor gradients and visualized as a heat map, using
269 the two strongest explanatory variables. Depending on the variable, exceedance can
270 mean the response variable being below or above a threshold, but always indicates
271 deterioration in ecological condition. When interpreting these heat maps, it should be
272 noted that the direction of the independent and interaction effects patterns within the
273 gradient of data, only, were used to construct the model.

274 The heat maps were constructed by calculating exceedance probabilities from the
275 model for a range of stressor combinations. For any values of the two stressors, the
276 model states that observed values of the response variable are normally distributed
277 with a mean of $b_0 + b_1x_1 + b_2x_2 + b_3x_1x_2$ and variance of $\sigma_S^2 + \sigma_Y^2 + \sigma_\epsilon^2$, where σ_S^2 is
278 the site-level random effect variance, σ_Y^2 is the year-level random effect variance and
279 σ_ϵ^2 is the residual variance. Note that for the datasets for which LM was used, this
280 variance simplifies to σ_ϵ^2 . The cumulative distribution function of the Gaussian
281 distribution was used to calculate the probability that an observed response value
282 drawn from this distribution exceeded the chosen threshold.

283 As well as heat maps, stressor scenario plots were produced showing the effects on
284 ecological indicators relative to critical thresholds of predicted changes in climate
285 change sensitive stressor indicators in the context of nutrient stressor indicators.
286 Scenarios were selected to allow visualization around the climate change projections
287 outlined above for the stressors included in the model outputs for each catchment. The
288 assessment of climate change effects for the Pinios Catchment is based on the
289 assumption that oxygen concentration will decrease as a result of prolonged drought
290 periods and higher water temperatures (Stefanidis et al., 2018). The scenario ranges
291 were, for Loch Leven: 0.0; -0.5; -1.0; and -1.5 mmday⁻¹ change in growing season
292 mean precipitation (0-60% decrease relative to mean value across data); Pinios
293 Catchment: 0.0; -0.5; -1.5; and -2.5 mgL⁻¹ change in autumn dissolved oxygen
294 concentration (0-30% decrease); Lepsämäenjoki Catchment: 0.0; +1.0; +2.0, and +3.0
295 °C change in mean growing season water temperature (0-17% increase). As above,
296 responses were quantified in terms of probability of threshold exceedance.

297 **3. Results**

298 **3.1 Loch Leven Catchment**

299 According to AIC values, the most parsimonious LM model for Loch Leven (Supp 1a)
300 indicated that annual mean chlorophyll *a* concentration was significantly related to
301 winter mean TP and growing season mean precipitation with no significant interaction
302 between them (Table 3). Although this was the best fitting model, there was also
303 substantial support for a model based on growing season and winter TP ($\Delta AIC_c =$
304 0.420, Supp 1a).

305 The heat maps created with the best fit model are shown in Figure 2. For the best fit
306 Loch Leven model, it is apparent that the highest effect and, therefore probability of
307 exceeding the critical value, occurs when growing season mean precipitation is lowest
308 and winter mean TP is highest.

309 We explored the effects of predicted changes in growing season mean precipitation,
310 linked to climate change, in the context of the model produced for Loch Leven (Figure
311 3). It is apparent that the greatest relative effect of decreasing growing season mean
312 precipitation on the probability of exceeding critical values of annual mean chlorophyll
313 *a* concentration occurs at the lowest winter mean TP concentrations. The projected
314 decrease of up to 20% (annual mean precipitation) in this region would equate to about
315 - 0.5 mm d⁻¹. Assuming this translates into a decrease during growing season mean
316 precipitation of the same value would result in an increased likelihood of failing the
317 critical value of about 10%; relative to no change; up to about 60 µg L⁻¹, after which
318 the scenario lines converge. The growing season mean chlorophyll *a* concentration
319 during the monitoring period was 42.09 µg L⁻¹ (Table 2).

320 **3.2 Pinios Catchment**

321 The most parsimonious LM for ASPT in the Pinios Catchment (Supp 1b) supported
322 effects of nitrate and dissolved oxygen concentrations, without interactions. Nitrate

323 concentration varied negatively and dissolved oxygen positively with ASPT. The model
324 comparison also provided support for alternative models based on nitrate alone (ΔAIC_c
325 = 0.331) and nitrate, pH and their interaction ($\Delta AIC_c = 1.962$).

326 The best fit model included a significant negative effect of nitrate and a significant
327 positive effect of dissolved oxygen (Table 3). The heat maps created with the best fit
328 model are shown (Figure 2) indicating that the probability of passing the critical value
329 remains high at dissolved oxygen concentrations above about 8 mg L⁻¹ regardless of
330 the NO₃-N concentration and that at low NO₃-N concentrations (i.e. near 0 mg L⁻¹) the
331 effect of DO is diminished.

332 The effects of predicted changes on the ASPT, linked with potential future changes in
333 dissolved oxygen, assumed here to reflect future climate change effects (Stefanidis et
334 al. 2018), are shown (Figure 3). A decrease in autumn mean dissolved oxygen
335 concentration of up to 2.5 mg L⁻¹ would result in about 20% increased likelihood of
336 failing the critical value for ASPT, relative to the no change scenario. This effect
337 appears to be consistent above about 2 mg L⁻¹ NO₃-N. The mean NO₃-N concentration
338 over the monitoring period was 2.21 mg L⁻¹.

339 **3.3 Lepsämänjoki Catchment**

340 The dredge analysis of LME models for summer mean chlorophyll a concentration in
341 the Lepsämänjoki Catchment (Supp 1c) indicated that the best fitting model had
342 effects of mean summer TP, mean summer water temperature and their interaction.
343 Four other model specifications had comparable support ($\Delta AIC_c < 2$), and all of these
344 included effects of summer water temperature and one other non-interacting stressor
345 (Supp 1c).

346 The best fit model indicated that chlorophyll a concentration increased with increasing
347 mean summer TP and water temperature and that these interacted synergistically
348 (Table 3, Figure 2). The probability of exceedance of the critical value was low below
349 about 16 °C regardless of summer mean water TP and the effect of temperature
350 diminished below about 100 µg L⁻¹ summer TP.

351 We explored the effects of predicted changes in summer mean water temperature,
352 linked to climate change (Figure 3). An increase of 1 °C in the mean summer
353 temperature would increase the probability of the critical threshold being exceeded by
354 about 10% at the mean annual TP concentration of 120 µg L⁻¹ (Table 2), relative to
355 the no change scenario. An increase of 2 °C would increase the likelihood of failure
356 by about 30% at the same TP concentration. The relative effects of the warming
357 scenarios increase, generally, with TP concentrations.

358 **4. Discussion**

359 The modelling approach reported provides a means of visualising and quantifying the
360 effects of paired stressors and their interactions on indicators of ecological responses.
361 We acknowledge that inclusion of a greater number of stressors would potentially
362 result in improved model fit and the discovery of higher order interactions.
363 Nevertheless, we have focussed our analysis to identify paired stressor interactions in
364 an attempt to provide relevant outputs for practical management considerations, which
365 require a level of simplification, focussing on nutrient enrichment and climate sensitive
366 stressor indicators. We have demonstrated that the approach can be used on a range
367 of data types, including temporal, spatiotemporal and spatial data across single or
368 multiple ecosystems. There is potential for the approach to be used across all
369 ecosystem types and all data types, including experimental data (Birk et al. 2020). We

370 outline the specific models, evidence from the literature to support their underlying
371 processes, and the relevance of the future stressor change analyses for future
372 management in each case study in the following sections.

373 **4.1 Effects of multiple and interacting stressors on each demonstration site**

374 Our model indicated that summer precipitation and winter TP acted additively on
375 growing season chlorophyll *a* concentration in Loch Leven, and that TP was the
376 dominant stressor. The model results agree generally with other studies in which the
377 drivers of water quality and chlorophyll *a* have been reported for Loch Leven. Carvalho
378 et al. (2012) associated a significant increase in spring *Daphnia* densities in recent
379 years to increases in water temperature that coincided with reductions in chlorophyll
380 *a* concentration and increases in water clarity in spring and early summer, indicating
381 higher order trophic interactions not explored here (Rigosi et al., 2014). At the same
382 time, high rainfall was associated with low chlorophyll *a* concentration, probably as a
383 result of increased flushing rate (Carvalho et al., 2012). However, May et al. (2017)
384 indicated that intense periods of rainfall also resulted in an increase of P load to Loch
385 Leven, although the ecological effects of this observation were not dominant in our
386 models. The winter TP concentration in Loch Leven is expected to reflect catchment
387 P loading to the lake, with summer conditions reflecting internal cycling of P between
388 bed sediments and the overlying water column (Sharpley et al., 2013). Spears et al.
389 (2006) explored the potential for hydrological regulation of Loch Leven to increase the
390 flushing rate in summer months to relinquish P associated with internal loading which
391 is manifest within the lake as a summer peak in TP. The model presented here
392 suggests that this would also be a sensible option for controlling phytoplankton
393 biomass which is not unsurprising given the strong correlation between TP and
394 chlorophyll *a* concentration in this lake. The model demonstrates well the capacity for

395 P control to be used to, at least in part, reduce the impact of future drier summers
396 although a reduction in the annual mean TP concentration even to 30 $\mu\text{g L}^{-1}$, would
397 still carry a 50% risk of failure of the WFD chlorophyll *a* target if summer precipitation
398 falls by only 1 mm day⁻¹.

399 For the Pinios catchment, nitrate and dissolved oxygen concentrations acted additively
400 on ASPT, and nitrate was the dominant stressor. These results are in agreement with
401 the findings from previous studies (Stefanidis et al., 2016a; 2018) where ASPT was
402 associated with nutrients and dissolved oxygen reflecting the ability of ASPT to capture
403 changes in the abiotic environment related to nutrient and organic pollution (e.g.
404 anoxic conditions). The role of nutrients, mainly nitrogen, on the occurrence of benthic
405 invertebrate taxa has been documented in numerous studies performed elsewhere in
406 Europe and the rest of the world (Johnson and Hering 2009; Villeneuve et al. 2015).
407 For instance, several studies have reported important relationships between nitrogen
408 species (TN, NH₄-N) and macroinvertebrate communities (Wang et al. 2007; Ashton
409 et al. 2014; Stefanidis et al. 2016a), confirming that nitrogen is a key predictor of the
410 ASPT metric. However, these relationships indicate an indirect effect of eutrophication
411 on macroinvertebrate communities although direct toxic effects of nitrate on specific
412 invertebrates are possible given high enough concentrations or exposure time
413 (Camargo et al., 2005). Laboratory studies have shown that nitrate concentrations of
414 10 mg L⁻¹, which is within the range observed in the study catchment, can have
415 adverse effects on sensitive aquatic animals (Camargo and Alonso 2006).
416 Furthermore, experimental studies have indicated that nutrient effects on stream
417 macroinvertebrates are indirect, affecting the food supply (e.g. periphyton) and thus
418 altering community composition (Elbrecht et al. 2016). In addition, under conditions of
419 nutrient surplus, excessive algal and microbial growth will lead to oxygen depletion

420 (Johnson and Hering 2009; Dahm et al. 2013). Lack of oxygen will have a direct effect
421 on aquatic animals, and a range of indicator species are especially sensitive to low
422 oxygen levels (e.g stonefly and mayfly taxa; Calapez et al. 2018). Since dissolved
423 oxygen concentration is inversely related to water temperature, warming is expected
424 to affect dissolved oxygen saturation (Cox and Whitehead 2009). Additionally, hypoxia
425 in running waters may occur not only because of organic pollution and eutrophication
426 but also due to drought and extreme low flow events, conditions that are becoming
427 more common in Southern Europe (Gudmundsson et al. 2017; Panagopoulos et al.
428 2019). We acknowledge that such complexities will be difficult to resolve in our
429 modelling approach, not least because of the potential for covariance between
430 stressors. In these circumstances, model outputs must be considered in the context
431 of comprehensive mechanistic understanding of the system of interest; and we use
432 our outputs, cautiously, to explore potential management implications below. We
433 highlight the need for targeted experimental studies to confirm cause and effect of
434 dominant stressors in such cases.

435 Prolonged periods of low flow or stagnation and high temperatures increase
436 productivity which in turn leads to the decomposition of the excessive organic material
437 and the depletion of oxygen levels (Marcarelli et al. 2010; Bernhardt et al. 2018). In
438 the Pinios Catchment, water overexploitation for irrigation combined with a dry climate
439 during summer maintains low river flows (Stefanidis et al. 2016b) while future climate
440 scenarios predict more frequent low flow and drought events (Stefanidis et al. 2018).
441 Thus, future climate change is expected to impact dissolved oxygen indirectly through
442 changes in the hydrologic regime and increased nutrient pollution but also directly due
443 to warming. These effects have been discussed by Stefanidis et al. (2016a; 2018) who
444 examined the impact of hydrologic alteration and nutrient enrichment on oxygen and

445 nitrate levels, confirming that these stressors are key predictors of benthic invertebrate
446 indices, including ASPT, in the Pinios Catchment. However, the form of the effect may
447 be expected to vary along the stressor gradient. For example, where dissolved oxygen
448 concentrations are reduced to very low levels then greater rates of denitrification may
449 occur, as demonstrated for shallow European lakes by Weyhenmeyer et al. (2019),
450 potentially increasing stress of low dissolved oxygen on macroinvertebrates whilst
451 relieving stress through NO₃-N. Nevertheless, no significant interaction term was
452 returned in our model; perhaps indicating that important interactions may lurk outside
453 of our data range.

454 The model for the Lepsämäenjoki Catchment showed that TP and water temperature
455 were the key factors controlling chlorophyll *a* concentration, indicating a significant
456 synergistic interaction effect (Rankinen et al. 2019). It is possible that light, here
457 measured as solar radiation, was not a limiting factor during the summer months due
458 to longer daylight hours at the higher latitudes (Lat 60 °N). Previous analyses have
459 indicated that agricultural water protection measures have reduced nutrient loads by
460 3% to 43% compared to mid-1980s (Rankinen et al., 2016). In this context, reductions
461 in nutrient concentrations may partly be attributed to a positive effect of warming on
462 forest growth, as longer and warmer growing seasons have improved nutrient uptake
463 in vegetation (Henttonen et al., 2017). However, a longer growing season may
464 increase the need to mitigate P, because rising temperatures may increase yields and
465 thus add pressures to intensify agriculture. This in turn, would increase the nutrient
466 load to rivers in this area (Rankinen et al., 2013).

467 According to the current Finnish agri-environmental programme, vegetation should be
468 removed from buffer zones at least once during growing season to remove excess
469 nutrients and to reduce dissolved P load (Aakkula et al. 2012). If the focus is also on

470 improving the ecological status of the river, our analysis suggests that other measures
471 around the river itself may also be necessary to achieve ecological quality targets
472 where nutrient enrichment is projected to increase. For example, the rise in water
473 temperature may be controlled through shading by allowing the growth of taller riparian
474 vegetation in buffer zones. It has been shown that shading by vegetation can decrease
475 water temperature by up to 3 °C (Garner et al. 2017; Loicq et al. 2018; Turunen et al.
476 2019). The benefits of riparian shading for maintaining low stream water temperatures
477 have been documented by several studies (e.g. Kristensen et al 2015; Dugdale et al
478 2018), although the technical details regarding the implementation of riparian shading
479 as a management measure are still vague (e.g. extent of cover, width of riparian strip,
480 etc.). Conversely, the reduction of water abstraction during the summer months could
481 act as a more feasible management option that may compensate for a decrease in
482 oxygen levels by ensuring higher flows and averting the risk of hypoxic events. Any
483 such measures require site scale assessment of effectiveness.

484 **4.2 Relevance for informing management of multiple stressors**

485 Our aim was to demonstrate a simple empirical modeling approach to allow the
486 detection of interactions between dominant paired (i.e. climate x nutrient) stressors in
487 three contrasting catchments. We confirm that in only one catchment was such an
488 interaction returned. In the sections above, we have presented mechanistic
489 understanding to aid with interpretation of the model outputs and in some cases we
490 identify that interactions may be expected to occur outside of our data ranges,
491 complicating management responses. Nevertheless, our model outputs offer scope
492 for future assessment of climate change related management; especially where
493 nutrient reduction measures are viewed as being achievable at the local scale.
494 Indicators of nutrient enrichment and climate change stress were important predictors

495 of ecological quality in the models for all catchments. However, we stress the need to
496 better understand the effects of projected climate change on relevant stressor
497 indicators at the catchment scale (Adrian et al., 2009). Two important sources of
498 uncertainty are relevant here. Firstly, the climate change projections, themselves,
499 carry significant uncertainty. Secondly, the effects of projected changes in local or
500 regional weather on stressors of ecological indicators can be difficult to constrain, as
501 discussed for the Pinios Catchment above.

502 Our analysis suggests, generally, that the projected decrease in precipitation in the
503 Loch Leven catchment could be, at least partly, addressed by a reduction in winter TP
504 concentrations. The greatest increase in probability of exceeding critical thresholds for
505 Loch Leven occurred at lower nutrient levels. In contrast, in the Lepsämäjoki
506 Catchment the effect of an increase in summer water temperature was most prominent
507 at higher nutrient levels. So the potential for nutrient reduction to address climate
508 change effects appears to be greatest at lower nutrient levels in the Loch Leven
509 Catchment but higher nutrient levels in the Lepsämäjoki Catchment.

510 Historically, management of water bodies has focussed on the control of single
511 stressors (Verdonschott et al., 2011) which are assumed to be dominant. This
512 approach is attractive in that it meets the practical needs of water managers, offering
513 a simple conceptual model; 'reduce the primary pressure and the ecosystem will
514 recover'. However, our results indicate that at the catchment scale secondary and
515 potentially interacting stressors may cause ecosystems to behave in a manner that is
516 unexpected when considering the single stressor management approach. Our models
517 derived from compulsory monitoring programmes (e.g. Munné et al., 2015) feature
518 relatively poor relationships with a lot of noise remaining unexplained. Thus, this
519 approach should be considered to offer initial conceptual understanding of ecosystem

520 behaviour allowing managers to systematically go beyond the primary stressor
521 approach to consider adaptive responses to future climate change and nutrient
522 enrichment (Pullin and Knight, 2009; Ryder et al., 2010).

523

524

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726 Table 1. Overview of interaction types and indication from model outputs considering two potentially
727 interacting stressors.

Type of interaction	Characterisation
Synergistic	Model coefficients for both stressors and their interaction all have the same sign (i.e. all positive or all negative)
Antagonistic	Model coefficients for both stressors have the same sign, but their interaction has the opposite sign
Opposing	Model coefficients for both stressors differ, sign of the interaction term not important

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733 Tables 2. Summary statistics for data included in the Loch Leven, Pinios, and Lepsämäjoki catchment
 734 analyses. Std. dev – standard deviation of the mean; Min – minimum of the range; Max – maximum of
 735 the range; N – number of computed values used in the analysis (e.g. one value per year for Loch Leven);
 736 EQI – ecological quality indicator; ASPT – average score per taxon value for macroinvertebrate
 737 community.

Variable	Season	Mean	St dev	Median	Min	Max	N
Loch Leven Catchment, UK							
Total phosphorus ($\mu\text{g L}^{-1}$)	Growing season	69.38	26.521	66	30.52	141.27	39
Total phosphorus ($\mu\text{g L}^{-1}$)	Autumn/Winter	60.57	15.679	60.47	29.69	88.2	39
Precipitation (mm day^{-1})	Growing season	2.415	0.641	2.352	1.307	4.262	39
Precipitation (mm day^{-1})	Autumn/Winter	3.022	0.627	2.931	1.705	4.234	39
Water temperature ($^{\circ}\text{C}$)	Growing season	15.05	0.966	15.25	12.1	17.36	39
Water temperature ($^{\circ}\text{C}$)	Autumn/Winter	5.742	0.807	5.769	4.059	7.313	39
Chlorophyll <i>a</i> ($\mu\text{g L}^{-1}$) – EQI	Annual	42.09	19.461	37.31	18.25	93.22	39
Pinios catchment, Greece							
$\text{PO}_4\text{-P}$ ($\mu\text{g L}^{-1}$)	Autumn	28.25	27.45	20.71	0.00	109.45	76
$\text{NO}_3\text{-N}$ (mg L^{-1})	Autumn	2.21	2.91	1.64	0.00	17.17	76
Dissolved oxygen (mg L^{-1})	Autumn	8.16	1.64	8.15	3.71	10.93	76
Water Temperature ($^{\circ}\text{C}$)	Autumn	16.85	2.79	17.65	8.30	20.80	76
pH	Autumn	8.00	0.46	7.97	6.27	8.64	76
Discharge ($\text{m}^3 \text{s}^{-1}$)	Autumn	3.79	2.84	2.95	0.00	8.54	76
ASPT – EQI	Autumn	4.74	1.33	4.69	1.67	7.44	76
Lepsämäjoki Catchment, Finland							
Total phosphorus ($\mu\text{g L}^{-1}$)	Growing season	120.65	48.07	113.45	41.5	349.33	177
Catchment run-off (mm day^{-1})	Growing season	4.17	3.03	3.26	0.48	17.38	177
Water temperature ($^{\circ}\text{C}$)	Growing season	17.92	1.70	17.94	13.77	22.15	177
Chlorophyll <i>a</i> ($\mu\text{g L}^{-1}$) – EQI	Growing season	18.61	19.67	12.63	1.4	142	177

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747 Table 3. Summary of fixed effects from models for each study system, explaining different ecological
 748 responses (Leven, Chlorophyll *a*; Pinios, ASPT; Lepsämäenjoki, Chlorophyll *a*). For each system, the
 749 optimal combination of two fixed effects from Table 2 and their interaction were selected based on
 750 AIC values. Also given are the adjusted R^2 calculated based on the likelihood-ratio tests against the
 751 intercept-only model.

	Estimate	se	<i>t</i>	<i>P</i>
Loch Leven Catchment, UK ($R^2_{adj} = 0.616$)				
Intercept	0.000	0.107	0.000	>0.999
Winter mean total phosphorous	0.610	0.117	5.200	<0.001
Growing season mean precipitation	-0.276	0.117	-2.355	0.024
Pinios Catchment, Greece ($R^2_{adj} = 0.352$)				
Intercept	0.000	0.095	0.000	>0.999
Nitrate concentration	-0.370	0.151	-2.449	0.017
Dissolved oxygen concentration	0.239	0.151	1.582	0.112
Lepsämäenjoki Catchment, Finland ($R^2_{adj} = 0.301$)				
Intercept	-0.011	0.134	-0.083	0.935
Summer mean total phosphorous	0.075	0.079	0.948	0.346
Summer mean water temperature	0.415	0.079	5.223	<0.001
Interaction (synergistic)	0.140	0.066	2.110	0.036

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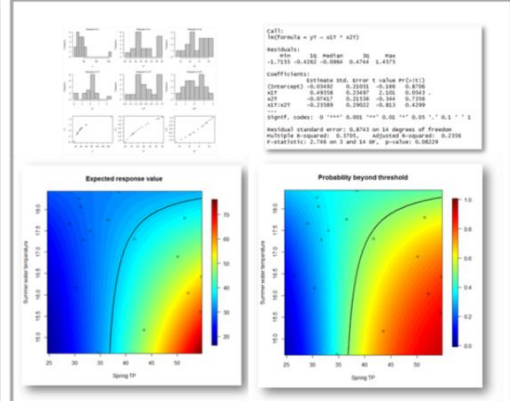
753 **Figure Legends**

754 Figure 1. General analytical framework for approach and description of assessment of risk factors
 755 including expected responses in relation to critical threshold and the probability that the critical
 756 threshold will be exceeded for a given stressor combination.

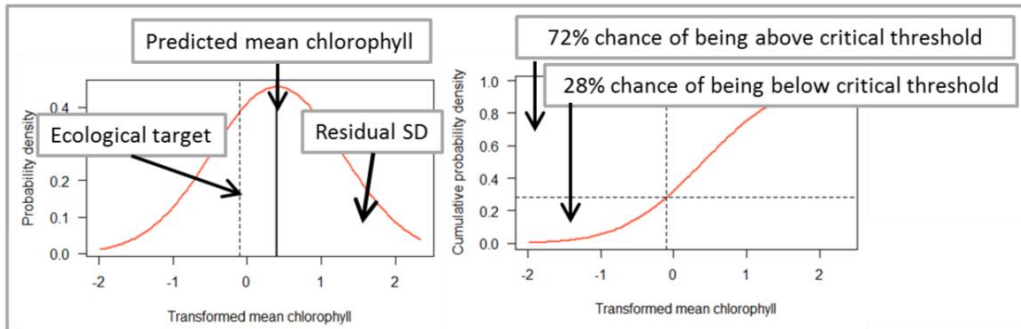
Decision flow

1. Construct model of main and interaction effects of temperature and phosphorus on chlorophyll
2. Set ecological target
3. Develop future stressor change scenario
4. Predict future values for stressors
5. Predict future ecological indicator response
6. Estimate distance from ecological target
7. Estimate confidence in prediction of distance from target

Model Construction

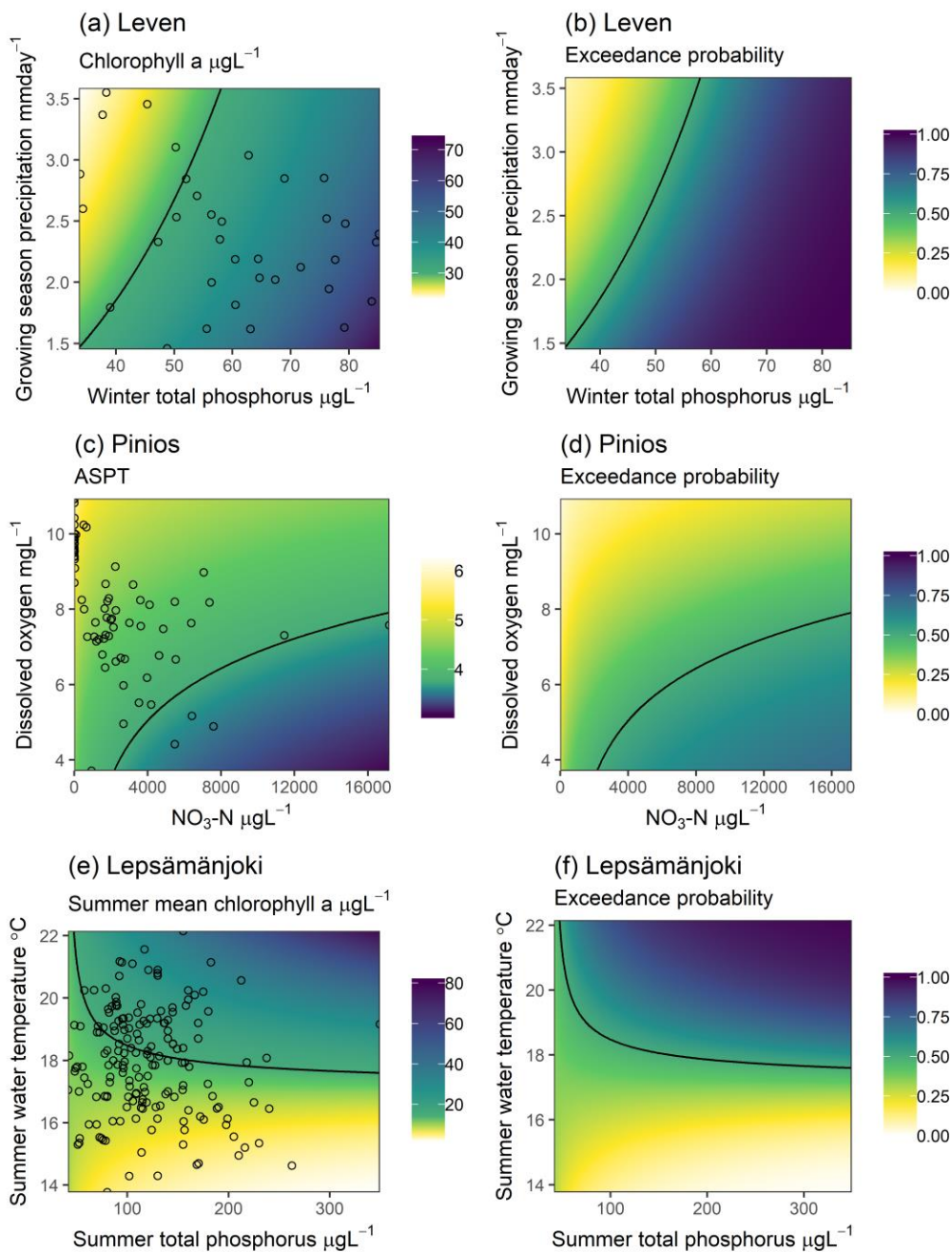


Model Application



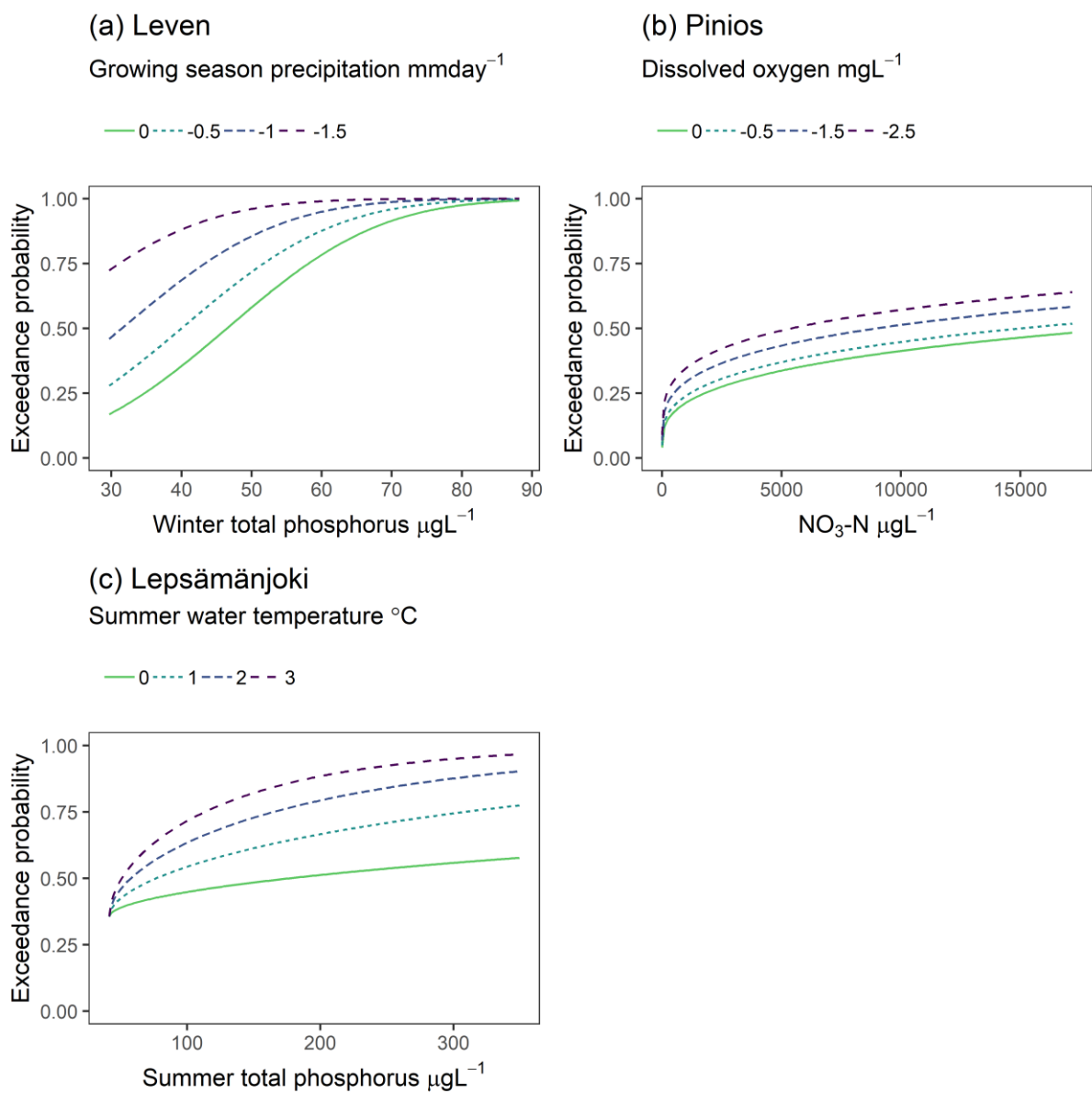
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761 Figure 2. Contour plots (a) and (b), Loch Leven, show the effects of winter total phosphorus (TP)
 762 concentration and growing season mean precipitation on the expected response in annual mean
 763 chlorophyll *a* concentration (left hand panel) and the probability of exceeding the critical value (right
 764 hand panel; the critical value, back line, is the WFD good/moderate target of 11 $\mu\text{g L}^{-1}$ annual mean
 765 chlorophyll *a* concentration). Contour plots (c) and (d), Pinios Catchment, showing the effects of
 766 nitrate concentration and dissolved oxygen concentration on the expected response in ASPT (left hand
 767 panel) and the probability of exceeding the critical value (right hand panel; the critical value, the black
 768 line, is the WFD good/moderate target of 4.81). Contour plots (e) and (f), Lepsämäjoki Catchment,
 769 show the effects of summer mean total phosphorus (TP) concentration and summer mean water
 770 temperature on the expected response annual mean chlorophyll *a* concentration (left hand panel) and
 771 the probability of exceeding the critical value (right hand panel; the critical value, the black line, is the
 772 WFD good/moderate target of 14.5 $\mu\text{g L}^{-1}$ summer mean chlorophyll *a* concentration).



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774 Figure 3. Climate change scenario assessments for Loch Leven (a), the Pinios Catchment (b) and the
 775 Lepsämäjoki Catchment (c). Evidence to support each scenario is provided in the methods section;
 776 they are considered realistic for each catchment. The assessment for Loch Leven assumes four levels
 777 of precipitation change and resultant effects on probability of exceeding the critical value for
 778 chlorophyll *a* concentration (i.e. the WFD good/moderate target of $11 \mu\text{g L}^{-1}$ annual mean chlorophyll
 779 *a* concentration) relative to the winter mean total phosphorus (TP) concentration. The Pinios
 780 Catchment assessment assumes four levels of DO change and resultant effects on probability of
 781 exceeding the critical value of ASPT (i.e. the WFD good/moderate target of 4.81) relative to the
 782 nitrogen concentration. The Lepsämäjoki Catchment assessment assumes four levels of temperature
 783 change and resultant effects on the probability of exceeding the critical value (i.e. the WFD
 784 good/moderate target of $14.5 \mu\text{g L}^{-1}$ summer mean chlorophyll *a* concentration) of chlorophyll *a*
 785 concentration relative to the summer mean total phosphorus (TP) concentration. All scenario levels
 786 are shown in the graph legends above each panel.



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