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

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Abstract

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

1. Introduction

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

It is clear that some stressors (e.g. nutrient enrichment) can be more easily manipulated at the local scale than others (Friberg et al., 2016). For example, catchment or ecosystem scale nutrient reduction has been demonstrated as an effective approach in lake restoration (Jeppesen et al., 2005; Spears et al., 2016). In contrast, other stressors acting on ecosystems but manifested from large-scale drivers, such as climate change, may be impossible for catchment managers to control. Stressors driven by anthropogenic activities operating at different scales can also interact, for example, changes in temperature and flushing rate can alter ecological responses to nutrient loading in rivers (Bowes et al., 2016) and lakes (Carvalho et al., 2012). In fact, it is widely acknowledged that many mechanisms exist through which the effects of climate change may be moderated in lakes and rivers including geographically distinct projections in weather patterns, in the influence of ecosystem morphology, and in the influence of other stressors, including nutrient enrichment (Adrian et al., 2009). As a result, some authors have suggested that disentangling these effects may be ‘challenging, if not infeasible’ (Benateau et al., 2019).

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

We currently lack robust statistical frameworks to detect and predict the effects of multiple stressor mitigation options at catchment scales. Such a framework would enable comparisons of frequency of occurrence and interaction forms across ecosystems, scales, and data types (e.g. experimental, spatial, temporal, spatiotemporal) common across routine monitoring programmes. Such a framework would enable comparisons of frequency of occurrence and interaction forms across ecosystems, scales, and data types (e.g. experimental, spatial, temporal, spatiotemporal) common across routine monitoring programmes. One important consideration is that data forms and frequency vary significantly between ecosystems. Feld et al. (2016) presented a synthesis of approaches for determining the presence of interactions between multiple stressors in freshwater ecosystems in this context, including the use of generalised linear mixed effects modelling (GLMM) and Birk et al. (2020) demonstrate that this approach is applicable to all forms of data to identify interaction forms (Table 1) across scales in fresh waters. Here we extend this approach to assess the probability of exceedance of water quality stressors when applied to future stressor change scenarios (e.g. Figure 1). This approach addresses two important statistical conditions necessary to underpin practical guidance to water managers: (1) that models should be constructed to determine interactions, specifically, and (2) that a standardized approach for model construction (i.e. stressor selection) is necessary. These conditions minimize bias in the model construct to improve representativeness and deliver the best 'model fit', statistically, whilst acknowledging the importance of scale and data quality as limiting factors in their application.

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

2. Methods

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

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

2.1.1 Loch Leven

Loch Leven, a shallow lake in the UK, offers a time series from a single sample site with roughly fortnightly sampling frequency between 1967 and 2017. Data were obtained from the Loch Leven long term monitoring dataset (May & Spears, 2012) across multiple years (1968-2013) with 39 years of data used in the final analysis as a result of missing values. In this study we consider the ecological response as chlorophyll *a* concentration in the water column, a proxy for phytoplankton concentration, as well as potential stressor indicators for nutrient enrichment (i.e. total phosphorus (TP) concentrations) and climate change (i.e. water temperature and precipitation) (Table 2). Water temperature, chlorophyll *a*, TP concentrations were determined roughly fortnightly during the monitoring period and processed to provide mean values as indicated in Table 2. Stressor data were averaged across growing season (May through September) and autumn/winter (October through April) with chlorophyll *a* averaged annually to be more in line with WFD methodology (Poikane et al., 2010). Methods for the determination of the Loch Leven indicators are described by Dudley et al. (2013), with the exception of precipitation data which were retrieved from the British Atmospheric Data Centre and processed from daily values representing local conditions as described by Carvalho et al. (2012). These indicators have been shown previously to play an important role in ecological community structure in Loch Leven (Ferguson et al., 2007).

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

As a result of climate change, by 2050 the east of Scotland is expected to experience a 1-2^{o}C rise in annual and summer average daily temperature, at the 10% probability level and assuming a medium emissions scenario (UKCP09 SRES A1B; Nakićenović et al., 2000). Under the same scenario, summer and winter precipitation is predicted to decrease by 20-30% and increase by 0-10%, respectively. More frequent and intense rainfall events are also predicted. O'Reilly et al. (2015) report an observed warming rate of about 0.7^{o}C per decade in Loch Leven surface waters.

Pinios Catchment, Greece

The Pinios Catchment represents multiple river monitoring data across 76 river monitoring sites collected during autumn (i.e. between September, October, November) 2002. The ecological response indicator used was Average Score Per Taxon (ASPT) calculated using macroinvertebrate taxon data from each site (Armitage et al., 1983). Climate change sensitive indicators included water temperature, discharge and dissolved oxygen concentration and indicators of nutrient enrichment included PO_4-P and NO_3-N concentrations. Other authors have confirmed the sensitivity of dissolved oxygen to climate change in fresh waters (Adrian et al., 2009; Benateau et al., 2019) where hypoxic events have been confirmed to coincide with droughts and low-flow conditions in the Pinios catchment. Target values for ASPT scores were set according to Lazaridou et al. (2016) and represent the 'good–moderate' boundary as defined by the EU WFD at 4.81. A description of the methods used for these determinands in the Pinios Catchment are available from Panagopoulos et al. (2014).

Climate change projections according to the most pessimistic scenario (RCP 8.5 rising emissions) predict an approximately 2 ^{o}C rise in mean annual air temperature and a 10% decrease in annual precipitation for the Pinios catchment by 2060 (Stefanidis et al., 2018). Assuming that projected increases in surface water temperatures are often 50 % to 70 % of the projected increases in air temperature (EEA, 2008), a 2 ^{o}C rise in mean annual air temperature could mean a 1.4 ^{o}C rise in water temperature. We assume here that these changes will result in a decrease in dissolved oxygen concentration as discussed in detail by Stefanidis et al. (2018).

2.1.2 Lepsämänjoki Catchment, Finland

The Lepsämänjoki Catchment (214 km^2) is a sub-basin of the Vantaanjoki River Basin in Southern Finland. It belongs to the Long-Term Ecosystem Research Network (http://www.lter-europe.net/lter-europe/about/organisation/facility-types/ltser-platforms) and is one of the best studied catchments in the drainage basins of the Gulf of Finland and the Archipelago Sea in the Baltic Sea. In contrast to other large catchments, these drainage basins consist of several small river catchments draining directly to the sea. Thus, the data set for the Lepsämänjoki Catchment was supplemented by measurements from the neighbouring catchments with similar soil and agricultural production types. The resulting data set represents 10 river sample sites which were sampled 7 to 25 times a year during the period 1985-2014. The ecological response indicator chosen for this catchment was summer mean chlorophyll *a* concentration. Climate change sensitive indicators included estimates of modelled catchment run-off and water temperature and nutrient enrichment indicators included TP concentration. The methods used for each of these determinands are described by Niemi et al. (2001). The target for summer mean chlorophyll *a* concentration was set at 14.5 µg L^{-1} using expert judgement.

The mean annual precipitation in the area is 650 mm, and the mean annual temperature is +4°C. In winter, temperature drops below 0^oC. Climate change projections, according to the most pessimistic scenario (RCP 8.5 rising emissions), predict an increase of approximately 2.5 °C in mean annual air temperature and less than 10% increase in annual precipitation by 2060. The increase is most highlighted in spring and autumn.

2.2 Data processing and model construction

2.2.1 Two-way interaction models

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

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_1 x_2 + S + Y + \epsilon$$

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

All models were fitted in R by maximum likelihood using the stats or lmerTest packages (Kuznetsova et al., 2017) for LM and LME models, respectively (R Core Team, 2020). Prior to model fitting the response variables and covariates were transformed to normal distributions using Box-Cox transformations, offset by a small value to ensure all values of the variable were greater than 0. This ensured the models met assumptions of normality of residuals, checked by examining model residual plots.

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

2.2.2 Risk of threshold exceedance

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

The heat maps were constructed by calculating exceedance probabilities from the model for a range of stressor combinations. For any values of the two stressors, the model states that observed values of the response variable are normally distributed 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 the site-level random effect variance, σ_Y^2 is the year-level random effect variance and σ_ϵ^2 is the residual variance. Note that for the datasets for which LM was used, this variance simplifies to σ_ϵ^2. The cumulative distribution function of the Gaussian distribution was used to calculate the probability that an observed response value drawn from this distribution exceeded the chosen threshold.

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

3. Results

3.1 Loch Leven Catchment

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

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

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

3.2 Pinios Catchment

The most parsimonious LM for ASPT in the Pinios Catchment (Supp 1b) supported effects of nitrate and dissolved oxygen concentrations, without interactions. Nitrate concentration varied negatively and dissolved oxygen positively with ASPT. The model comparison also provided support for alternative models based on nitrate alone (ΔAIC_c = 0.331) and nitrate, pH and their interaction (ΔAIC_c = 1.962).

The best fit model included a significant negative effect of nitrate and a significant positive effect of dissolved oxygen (Table 3). The heat maps created with the best fit model are shown (Figure 2) indicating that the probability of passing the critical value remains high at dissolved oxygen concentrations above about 8 mg L^{-1} regardless of the NO_3-N concentration and that at low NO_3-N concentrations (i.e. near 0 mg L^{-1}) the effect of DO is diminished.

The effects of predicted changes on the ASPT, linked with potential future changes in dissolved oxygen, assumed here to reflect future climate change effects (Stefanidis et al. 2018), are shown (Figure 3). A decrease in autumn mean dissolved oxygen concentration of up to 2.5 mg L^{-1} would result in about 20% increased likelihood of failing the critical value for ASPT, relative to the no change scenario. This effect appears to be consistent above about 2 mg L^{-1} NO_3-N. The mean NO_3-N concentration over the monitoring period was 2.21 mg L^{-1}.

3.3 Lepsämänjoki Catchment

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

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

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

4. Discussion

The modelling approach reported provides a means of visualising and quantifying the effects of paired stressors and their interactions on indicators of ecological responses. We acknowledge that inclusion of a greater number of stressors would potentially result in improved model fit and the discovery of higher order interactions. Nevertheless, we have focussed our analysis to identify paired stressor interactions in an attempt to provide relevant outputs for practical management considerations, which require a level of simplification, focussing on nutrient enrichment and climate sensitive stressor indicators. We have demonstrated that the approach can be used on a range of data types, including temporal, spatiotemporal and spatial data across single or multiple ecosystems. There is potential for the approach to be used across all ecosystem types and all data types, including experimental data (Birk et al. 2020). We outline the specific models, evidence from the literature to support their underlying processes, and the relevance of the future stressor change analyses for future management in each case study in the following sections.

4.1 Effects of multiple and interacting stressors on each demonstration site

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

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

For the Pinios catchment, nitrate and dissolved oxygen concentrations acted additively on ASPT, and nitrate was the dominant stressor. These results are in agreement with the findings from previous studies (Stefanidis et al., 2016a; 2018) where ASPT was associated with nutrients and dissolved oxygen reflecting the ability of ASPT to capture changes in the abiotic environment related to nutrient and organic pollution (e.g. anoxic conditions). The role of nutrients, mainly nitrogen, on the occurrence of benthic invertebrate taxa has been documented in numerous studies performed elsewhere in Europe and the rest of the world (Johnson and Hering 2009; Villeneuve et al. 2015). For instance, several studies have reported important relationships between nitrogen species (TN, NH_4-N) and macroinvertebrate communities (Wang et al. 2007; Ashton et al. 2014; Stefanidis et al. 2016a), confirming that nitrogen is a key predictor of the ASPT metric. However, these relationships indicate an indirect effect of eutrophication on macroinvertebrate communities although direct toxic effects of nitrate on specific invertebrates are possible given high enough concentrations or exposure time (Camargo et al., 2005). Laboratory studies have shown that nitrate concentrations of 10 mg L^{-1}, which is within the range observed in the study catchment, can have adverse effects on sensitive aquatic animals (Camargo and Alonso 2006). Furthermore, experimental studies have indicated that nutrient effects on stream macroinvertebrates are indirect, affecting the food supply (e.g. periphyton) and thus altering community composition (Elbrecht et al. 2016). In addition, under conditions of nutrient surplus, excessive algal and microbial growth will lead to oxygen depletion

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

Prolonged periods of low flow or stagnation and high temperatures increase productivity which in turn leads to the decomposition of the excessive organic material and the depletion of oxygen levels (Marcarelli et al. 2010; Bernhardt et al. 2018). In the Pinios Catchment, water overexploitation for irrigation combined with a dry climate during summer maintains low river flows (Stefanidis et al. 2016b) while future climate scenarios predict more frequent low flow and drought events (Stefanidis et al. 2018). Thus, future climate change is expected to impact dissolved oxygen indirectly through changes in the hydrologic regime and increased nutrient pollution but also directly due to warming. These effects have been discussed by Stefanidis et al. (2016a; 2018) who examined the impact of hydrologic alteration and nutrient enrichment on oxygen and nitrate levels, confirming that these stressors are key predictors of benthic invertebrate indices, including ASPT, in the Pinios Catchment. However, the form of the effect may be expected to vary along the stressor gradient. For example, where dissolved oxygen concentrations are reduced to very low levels then greater rates of denitrification may occur, as demonstrated for shallow European lakes by Weyhenmeyer et al. (2019), potentially increasing stress of low dissolved oxygen on macroinvertebrates whilst relieving stress through NO_3-N. Nevertheless, no significant interaction term was returned in our model; perhaps indicating that important interactions may lurk outside of our data range.

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

According to the current Finnish agri-environmental programme, vegetation should be removed from buffer zones at least once during growing season to remove excess nutrients and to reduce dissolved P load (Aakkula et al. 2012). If the focus is also on improving the ecological status of the river, our analysis suggests that other measures around the river itself may also be necessary to achieve ecological quality targets where nutrient enrichment is projected to increase. For example, the rise in water temperature may be controlled through shading by allowing the growth of taller riparian vegetation in buffer zones. It has been shown that shading by vegetation can decrease water temperature by up to 3 °C (Garner et al. 2017; Loicq et al. 2018; Turunen et al. 2019). The benefits of riparian shading for maintaining low stream water temperatures have been documented by several studies (e.g. Kristensen et al 2015; Dugdale et al 2018), although the technical details regarding the implementation of riparian shading as a management measure are still vague (e.g. extent of cover, width of riparian strip, etc.). Conversely, the reduction of water abstraction during the summer months could act as a more feasible management option that may compensate for a decrease in oxygen levels by ensuring higher flows and averting the risk of hypoxic events. Any such measures require site scale assessment of effectiveness.

4.2 Relevance for informing management of multiple stressors

Our aim was to demonstrate a simple empirical modeling approach to allow the detection of interactions between dominant paired (i.e. climate x nutrient) stressors in three contrasting catchments. We confirm that in only one catchment was such an interaction returned. In the sections above, we have presented mechanistic understanding to aid with interpretation of the model outputs and in some cases we identify that interactions may be expected to occur outside of our data ranges, complicating management responses. Nevertheless, our model outputs offer scope for future assessment of climate change related management; especially where nutrient reduction measures are viewed as being achievable at the local scale. Indicators of nutrient enrichment and climate change stress were important predictors of ecological quality in the models for all catchments. However, we stress the need to better understand the effects of projected climate change on relevant stressor indicators at the catchment scale (Adrian et al., 2009). Two important sources of uncertainty are relevant here. Firstly, the climate change projections, themselves, carry significant uncertainty. Secondly, the effects of projected changes in local or regional weather on stressors of ecological indicators can be difficult to constrain, as discussed for the Pinios Catchment above.

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

Historically, management of water bodies has focussed on the control of single stressors (Verdonschott et al., 2011) which are assumed to be dominant. This approach is attractive in that it meets the practical needs of water managers, offering a simple conceptual model; ‘reduce the primary pressure and the ecosystem will recover’. However, our results indicate that at the catchment scale secondary and potentially interacting stressors may cause ecosystems to behave in a manner that is unexpected when considering the single stressor management approach. Our models derived from compulsory monitoring programmes (e.g. Munné et al., 2015) feature relatively poor relationships with a lot of noise remaining unexplained. Thus, this approach should be considered to offer initial conceptual understanding of ecosystem behaviour allowing managers to systematically go beyond the primary stressor approach to consider adaptive responses to future climate change and nutrient enrichment (Pullin and Knight, 2009; Ryder et al., 2010).

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Table 1. Overview of interaction types and indication from model outputs considering two potentially 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

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

Variable	Season	Mean	St dev	Median	Min	Max	N
Loch Leven Catchment, UK							
Total phosphorus (µg L^{-1})	Growing season	69.38	26.521	66	30.52	141.27	39
Total phosphorus (µg 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 (°C)	Growing season	15.05	0.966	15.25	12.1	17.36	39
Water temperature (°C)	Autumn/Winter	5.742	0.807	5.769	4.059	7.313	39
Chlorophyll *a* (µg L^{-1}) – EQI	Annual	42.09	19.461	37.31	18.25	93.22	39
Pinios catchment, Greece							
PO_4-P (µg L^{-1})	Autumn	28.25	27.45	20.71	0.00	109.45	76
NO_3-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 (ºC)	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 (m^3 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
Lepsämänjoki Catchment, Finland							
Total phosphorus (µg 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 (°C)	Growing season	17.92	1.70	17.94	13.77	22.15	177
Chlorophyll a (µg L^{-1}) – EQI	Growing season	18.61	19.67	12.63	1.4	142	177

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

	Estimate	se	*t*	*P*
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
Lepsämänjoki 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

Figure Legends

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

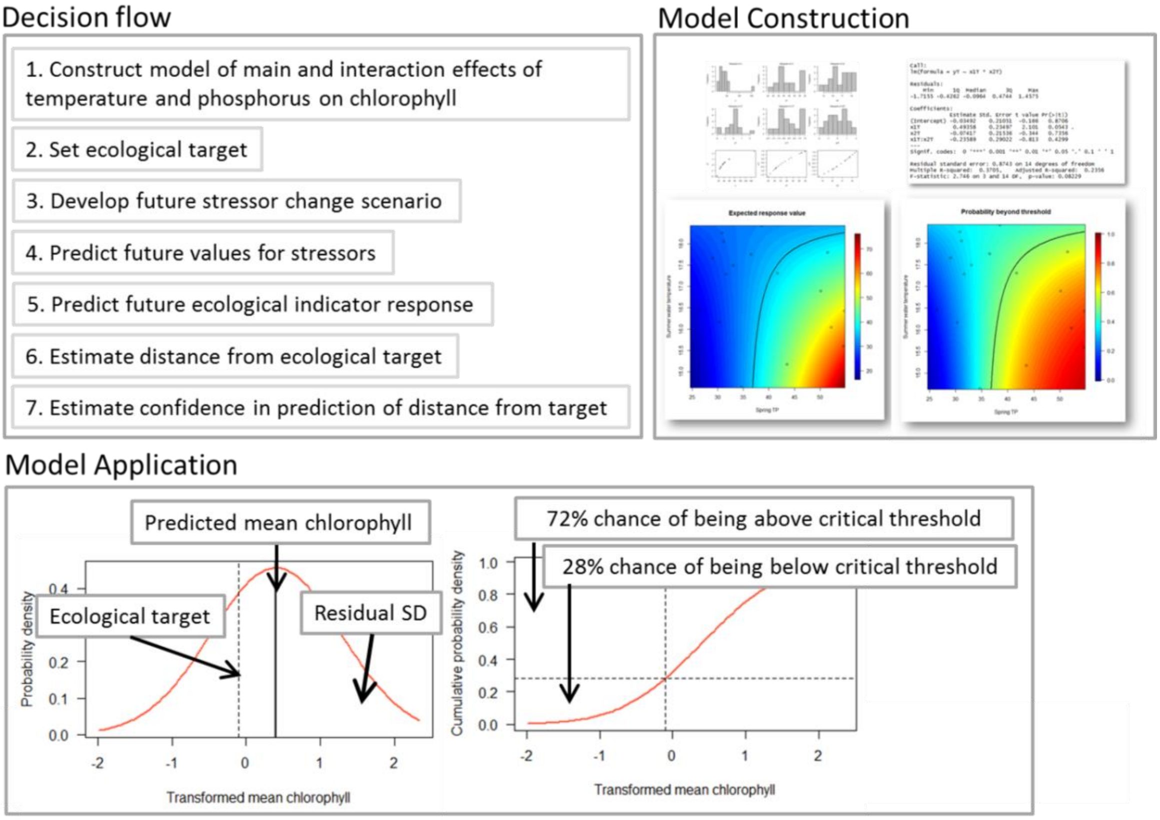

Figure 2. Contour plots (a) and (b), Loch Leven, show the effects of winter total phosphorus (TP) concentration and growing season mean precipitation on the expected response in annual mean chlorophyll *a* concentration (left hand panel) and the probability of exceeding the critical value (right hand panel; the critical value, back line, is the WFD good/moderate target of 11 µg L^{-1} annual mean chlorophyll *a* concentration). Contour plots (c) and (d), Pinios Catchment, showing the effects of nitrate concentration and dissolved oxygen concentration on the expected response in ASPT (left hand panel) and the probability of exceeding the critical value (right hand panel; the critical value, the black line, is the WFD good/moderate target of 4.81). Contour plots (e) and (f), Lepsämänjoki Catchment, show the effects of summer mean total phosphorus (TP) concentration and summer mean water temperature on the expected response annual mean chlorophyll *a* concentration (left hand panel) and the probability of exceeding the critical value (right hand panel; the critical value, the black line, is the WFD good/moderate target of 14.5 µg L^{-1} summer mean chlorophyll *a* concentration).

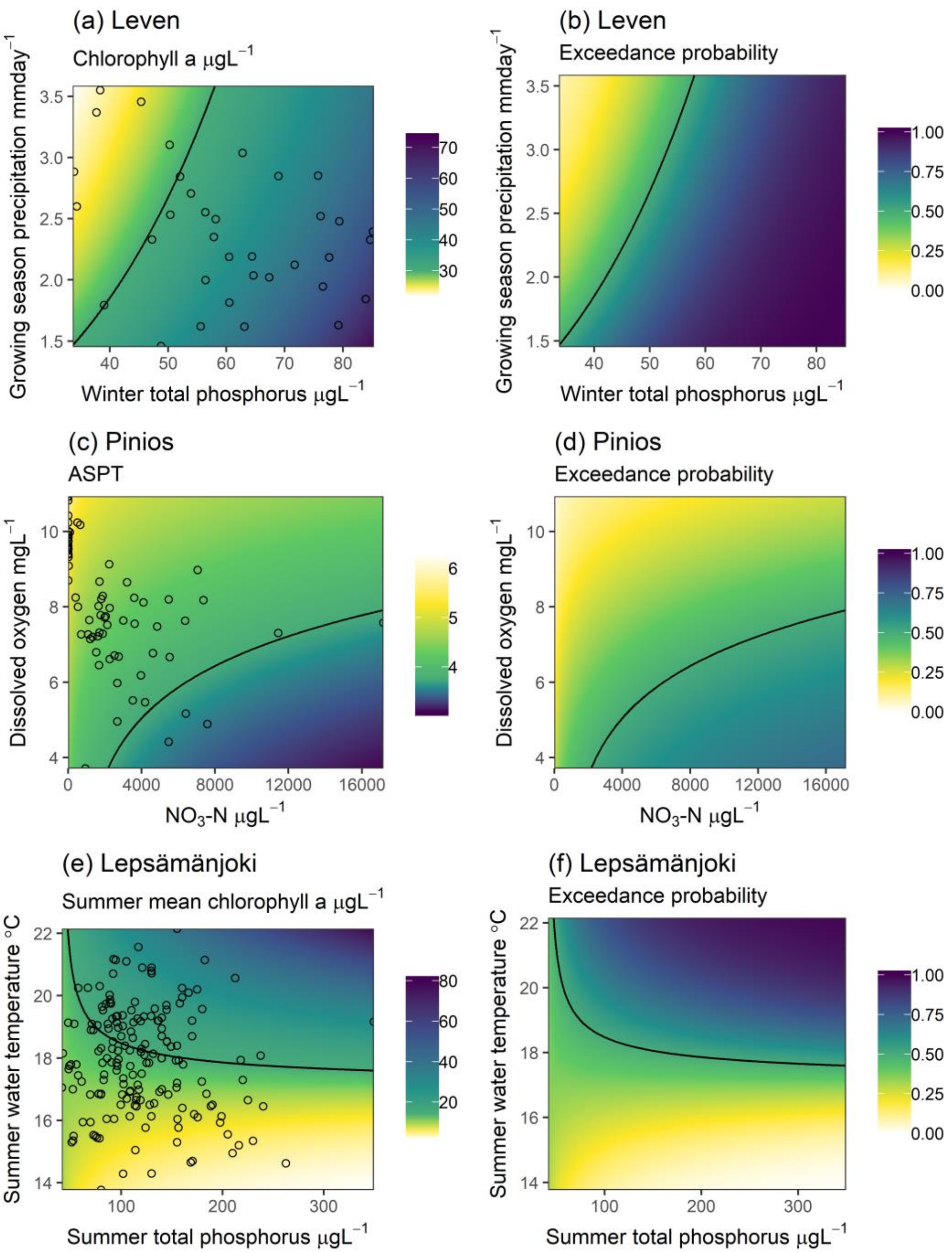

Figure 3. Climate change scenario assessments for Loch Leven (a), the Pinios Catchment (b) and the Lepsämänjoki Catchment (c). Evidence to support each scenario is provided in the methods section; they are considered realistic for each catchment. The assessment for Loch Leven assumes four levels of precipitation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