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RESEARCH ARTICLE

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Climate warming shifts riverine macroinvertebrate communities to be more sensitive to chemical pollutants

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Abstract

Freshwaters are highly threatened ecosystems that are vulnerable to chemical pollution and climate change. Freshwater taxa vary in their sensitivity to chemicals and changes in species composition can potentially affect the sensitivity of assemblages to chemical exposure. Here we explore the potential consequences of future climate change on the composition and sensitivity of freshwater macroinvertebrate assemblages to chemical stressors using the UK as a case study. Macroinvertebrate assemblages under end of century (2080–2100) and baseline (1980–2000) climate conditions were predicted for 608 UK sites for four climate scenarios corresponding to mean temperature changes of 1.28 to 3.78°C. Freshwater macroinvertebrate toxicity data were collated for 19 chemicals and the hierarchical species sensitivity distribution model was used to predict the sensitivity of untested taxa using relatedness within a Bayesian approach. All four future climate scenarios shifted assemblage compositions, increasing the prevalence of Mollusca, Crustacea and Oligochaeta species, and the insect taxa of Odonata, Chironomidae, and Baetidae species. Contrastingly, decreases were projected for Plecoptera, Ephemeroptera (except for Baetidae) and Coleoptera species. Shifts in taxonomic composition were associated with changes in the percentage of species at risk from chemical exposure. For the 3.78°C climate scenario, 76% of all assemblages became more sensitive to chemicals and for 18 of the 19 chemicals, the percentage of species at risk increased. Climate warming-induced increases in sensitivity were greatest for assemblages exposed to metals and were dependent on baseline assemblage composition, which varied spatially. Climate warming is predicted to result in changes in the use, environmental exposure and toxicity of chemicals. Here we show that, even in the absence of these climate-chemical interactions, shifts in species composition due to climate warming will increase chemical risk and that the impact of chemical pollution on freshwater macroinvertebrate biodiversity may double or quadruple by the end of the 21st century.

KEYWORDS
chemicals, climate change, ecotoxicology, freshwater, macroinvertebrates, modelling, pollution

1 | INTRODUCTION

Freshwaters are disproportionately diverse ecosystems representing 0.8% of the planet's surface but around 6% of described species (Dudgeon et al., 2006). However, freshwater biodiversity is reducing with vertebrate populations declining by an average of 83% since 1970 (WWF, 2016) and a third of freshwater insects being threatened with extinction (Sánchez-Bayo & Wyckhuys, 2019). Freshwater ecosystems are subject to multiple anthropogenic stressors, including chemical pollution and climate change (Birk et al., 2020), which are predicted to become more severe over the 21st century (Persson et al., 2022; Reid et al., 2019). For instance, average global temperatures are predicted to rise by 1.7 to 4.8°C in 2100 (IPCC, 2022) and are set to become one of the largest stressors to freshwater ecosystems independently and through interacting with other stressors such as chemical pollutants (Maxwell et al., 2016).

Although the impacts of chemical-temperature interactions on aquatic organisms have been studied for over 50 years (Cairns et al., 1972) and there has been a recent increased interest in the effect of global warming on the toxicity of chemicals (Arnell et al., 2021; Kibria et al., 2021), the literature is dominated by studies investigating effects on individual organisms, generally under laboratory conditions, with some mesocosm experiments performed (Cabral et al., 2019; Pinheiro et al., 2021). Consequently, there is proportionally less known about the interaction between climate change and sensitivity above the individual organism level.

Chemical sensitivity is species specific (Vaal et al., 2000) and therefore factors that change species distributions and alter the composition of freshwater assemblages, have the potential to alter their chemical sensitivity. Global warming has been associated with changes in macroinvertebrate community structure (Baranov et al., 2020) is predicted to affect the distribution of over one third of fish species (Barbarossa et al., 2021) and contribute to the decline of almost half of current freshwater fish species (Manjarrés et al., 2021). However, the potential consequences of climate-induced changes in community composition on the future sensitivity of freshwater assemblages to chemical stressors has not been investigated.

Here, we address this knowledge gap using macroinvertebrate communities in UK rivers as a case study. Freshwater macroinvertebrates are taxonomically diverse and exhibit a wide range of sensitivities to chemical stressors, leading to their use as indicators of freshwater quality (Berger et al., 2017; Grizzetti et al., 2019). However, understanding of how species composition translates into chemical sensitivity of ecosystems is severely limited (Gessner & Tlili, 2016). The overall sensitivity of an assemblage to a chemical can be calculated from the sensitivity profile of the constituent species using methods such as species sensitivity distributions (SSDs). SSDs are statistical models that describe the profile of sensitivity for a collection of species based on single-species toxicity data (Posthuma et al., 2001). However, the application of SSDs to naturally occurring species assemblages is limited by data availability; chemical-specific toxicity data are only available for a limited number of species and therefore the sensitivity of most species in ecosystems is unknown (Peters et al., 2014).

The extrapolation of toxicity data to untested species is an area of active research (Van den Berg et al., 2021) and three main types of approaches can be identified: trait-based (Ippolito et al., 2012; Rubach et al., 2010; Van den Berg et al., 2019), relatedness-based (Craig, 2013; Guenard et al., 2014; Malaj et al., 2016) and genomics-based (LaLone et al., 2013). Trait-based approaches have been used to investigate spatial variation in the sensitivity of freshwater invertebrates to chemical stressors, although the analysis was restricted to narcotic and acetylcholine-inhibiting toxicants due to the limited availability of relevant trait data (Van den Berg et al., 2020). Relatedness-based approaches are less constrained by data availability as they can use readily available information from global taxonomy databases (e.g., National Center for Biotechnology Information [NCBI] Taxonomy database [https://www.ncbi.nlm.nih.gov], Integrated Taxonomic Information System [https://www.itis.gov/]) and can therefore be applied, in principle, to all chemical stressors (Van den Berg et al., 2021). Here, we use a hierarchical SSD (hSSD) model based on taxonomic relatedness to predict toxicity data for untested species and generate assemblage-specific sensitivity profiles (Craig, 2013). This novel approach allows us to calculate the sensitivity of specific assemblages to toxic chemicals and to explore how the chemical sensitivity of freshwater macroinvertebrate assemblages may change in a warming world.

To investigate the impact of climate-induced changes in community composition on the future sensitivity of freshwater assemblages to chemical stressors, it is necessary to predict the future composition of macroinvertebrate assemblages. Several regional multivariate models have been developed to predict the composition of macroinvertebrate assemblages based on a subset of environmental data (Davy-Bowker et al., 2006; Johnson & Sandin, 2001; Poquet et al., 2009; Simpson & Norris, 2000). These models are based on the River Invertebrate Prediction and Classification System (RIVPACS), which predicts the macroinvertebrate species expected to occur at a UK river site if it was minimally impacted (Clarke et al., 2003). The latest version of the RIVPACS model (RIVPACS IV) is incorporated into the River Invertebrate Classification Tool (RICT; Environment Agency et al., 2021). As temperature is one of the environmental variables used to predict macroinvertebrate assemblages, RICT could potentially be used to predict assemblages under future climates.

Previous research into the combined effects of temperature and chemical exposure has focused on effects at the organism scale. However, the need for more research into how change in biodiversity from temperature will affect the future risk chemicals pose to the environment is recognised. By the end of the 21st century, average UK temperatures are projected to rise between 1.28 and 3.78°C depending on the climate scenario. Climate warming is expected to change the use, environmental exposure and toxicity of chemicals (Biswas et al., 2018; Martínez-Megías et al., 2023; Op de Beeck et al., 2018). However, here we address the hypothesis that climate-induced changes in the species composition of assemblages will alter the risk of chemical pollution to biodiversity even in the absence of changes in chemical use, exposure or toxicity. We use spatially explicit climate predictions coupled with novel applications of the RICT and hSSD models to predict the composition and sensitivity of UK freshwater macroinvertebrate assemblages to toxic chemicals predicted under end of 21st century climates. We demonstrate how these changing assemblages will shift their sensitivity to toxic chemicals on a chemical-by-chemical basis, highlighting the need to account for multiple effects of temperature beyond the individual level when considering the future risk of chemicals to the environment.

2 | METHODOLOGY

2.1 | Effect of temperature change on the composition of macroinvertebrate assemblages

The case study comprised 608 minimally impacted sites across mainland Great Britain and Northern Ireland (Figure 1) and focused on two time periods: 1981–2000 (baseline) and 2080–2099 (future). Four climate scenarios were investigated, corresponding to the emissions scenarios of the IPCC's representative concentration pathways: RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5 (IPCC, 2022). RICT (available at: https://www.fba.org.uk/rivpacs-and-rict/river-invertebrate-classification-tool) was used to predict baseline and four future macroinvertebrate assemblages for each of the study sites, giving a total of 3040 assemblages.

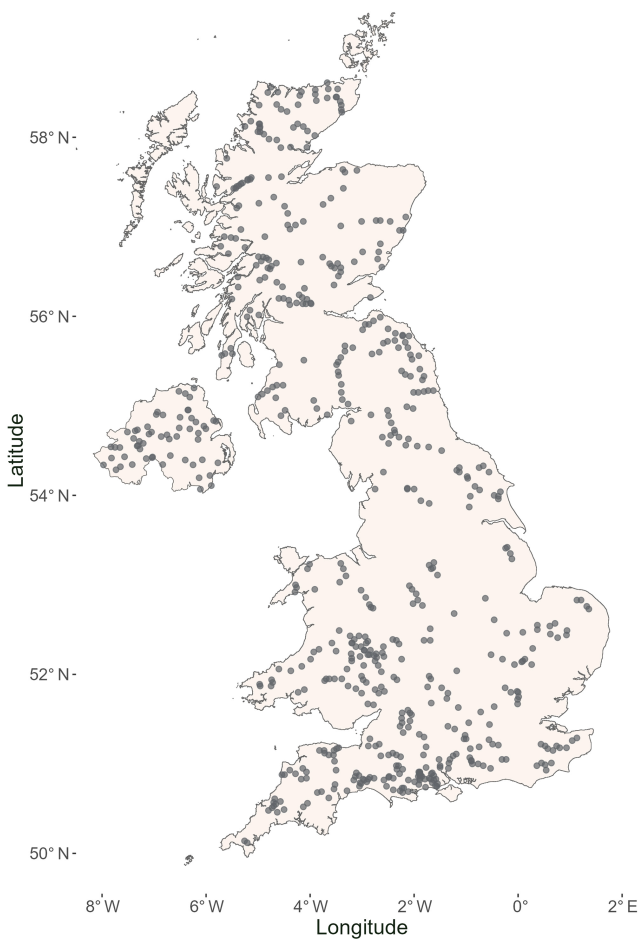

FIGURE 1 Location of the 608 reference sites across mainland Great Britain and Northern Ireland used for predicting macroinvertebrate assemblages.

RICT uses environmental data to predict the macroinvertebrate species expected at a site if it was minimally impacted (Clarke et al., 2003) and is the standard tool used to assess water quality in the UK. By adjusting site-specific temperatures to those expected by the end of the century under climate change, it was possible to use the tool to predict future species compositions (Armitage, 2000). Except for temperature, all site-specific environmental predictors (i.e., latitude, longitude, distance from source, stream width, stream depth, discharge category, alkalinity, slope at site and mean substratum composition) were kept constant between baseline and future predictions.

RICT predictions are based on mean daily air temperature and air temperature range (UKTAG, WFD, 2008). Baseline predictions of macroinvertebrate assemblages used temperature data collected by the Met Office over a 30-year period based on a 50 km grid across the UK (Cox et al., 1997; Wright et al., 1989). Future predictions of macroinvertebrate assemblages for each of the four climate scenarios used temperature data for 2080–2099 derived from the 2019 update of the UKCP18 projections (Met Office, 2019). The spatial resolution of UKCP18 temperature projections for the four climate scenarios is 25 km, and the predicted values were an increase in temperature compared to the baseline period of 1981–2000. Temperature predictions based either on a 25 km or 50 km scale were strongly correlated (Table S1). The mean daily air temperature and air temperature range averaged across the year, were extracted from the 25 km grid square corresponding to each of the study sites for each year from 2080 to 2099. These annual values were then averaged to give a site-specific 20-year mean annual average increase in daily air temperature and a 20-year mean annual change to air temperature range for each climate scenario. After adding the future changes to temperature and range, the four climate scenarios corresponded to a mean temperature change across the study sites between 1981–2000 and 2080–2099 of 1.28°C (RCP 2.6), 2.32°C (RCP 4.5), 2.70°C (RCP 6.0), and 3.78°C (RCP 8.5).

Taxonomic level 4 of RICT predicted the probability of occurrence at a site of 229 macroinvertebrate taxa (Davy-Bowker et al., 2008). A minimum probability of occurrence of 0.4 (in line with endgroup selection for RIVPACS III) was used to compile predicted macroinvertebrate assemblages under baseline and the four future climate scenarios for each of the study sites. For each taxon in the predicted assemblages, a full taxonomy (kingdom, phylum, class, order, family, genus, species) was constructed using the package taxize and the NCBI database (Chamberlain & Szöcs, 2013; Schoch et al., 2020, available at: https://www.ncbi.nlm.nih.gov/taxonomy). The taxonomic similarity between each of the predicted future assemblages and its corresponding baseline assemblage was measured using the Jaccard index ($J(A, B) = |A \cap B| / |A \cup B|$) and non-metric multidimensional scaling (NMDS) was used to visualise the Jaccard similarity index between the 3040 assemblages. Minimum stress from the NMDS was 0.045 indicating suitable structuring. For each future climate scenario, a permutational multivariate analysis of variance (PERMANOVA) was used to assess whether the composition of assemblages across the five groups differed statistically from baseline. All analyses were undertaken in R using the vegan package (Oksanen et al., 2013).

The net gain of different taxonomic groups across the 608 sites was calculated for each climate scenario. All unique taxa in a site were listed for the baseline and four future scenarios. Where a taxon was present in a future scenario but not in the baseline was considered a gain and where a taxon was present in the baseline but not in the future scenario was considered a loss. Gains and losses were then pooled by taxonomic rank, ensuring that there were at least three different families or genera present in the group across the 608 sites. Taxonomy grouping was at the phylum level for Mollusca, class level for Malacostraca, Oligochaeta and Clitellata and order level for Insecta. The dominant families within the Diptera (i.e., Chironomidae) and Ephemeroptera (i.e., Baetidae) were analysed separately due to non-uniform responses to warming. The taxa gains and losses for each of the 12 taxonomic groups (Baetidae, Chironomidae, Clitellata, Coleoptera, Malacostraca, Mollusca, Odonata, Oligochaeta, Other Diptera, Other Ephemeroptera, Plecoptera and Trichoptera) were summed across the 608 sites for every future scenario to give a net change value.

2.2 | Toxicity data and model fit

Acute toxicity data were extracted from the US EPA ECOTOXicology Knowledgebase (Olker et al., 2022, available at http://www.epa.gov/ecotox/) and from Maltby et al., 2005. EC_{50} (immobility) or LC_{50} (mortality) values for aqueous exposure durations of 1–7 day were extracted for macroinvertebrates exposed to 19 chemicals including heavy metals and insecticides. Toxicity data based on measured concentrations were prioritised and formulation toxicity data were excluded. Data reported as > or <were collated but not used in the subsequent analyses. The lowest toxicity value reported was used for each study, and the geometric mean was calculated when multiple studies reported data for the same species and endpoint. Outliers were checked by consulting original references. The criteria for chemical selection were: (1) toxicity data available for at least 15 different taxa including representatives of the major invertebrate phyla found in UK freshwater ecosystems (i.e., Annelida, Arthropoda, Mollusca); (2) fit to the hSSD model (full model description in Supporting Information S2) assessed using leave-one-out analyses (Table S2).

2.3 | Predicting the effect of climate change on assemblage sensitivity

The hSSD model (version 122b) was used for each of the 19 study chemicals to predict toxicity values for all macroinvertebrate taxa in the baseline or future climate scenario assemblages at the 608 study sites (i.e., total species pool). The hSSD model is a Bayesian based model that uses Markov chain Monte Carlo (MCMC) to sample from a distribution representing uncertainty about the sensitivity of the taxa in the total species pool, taking into account the available toxicity data for the chemical and taxonomy (Craig, 2013).

To address the research questions, the outputs of the hSSD need to be used to quantify the sensitivity of each assemblage, acknowledging that assemblages will exhibit variation in both taxonomic composition and the number of species present. Therefore, the measure used for an assemblage must represent the taxonomic composition while being neutral to assemblage size. Additionally, as regulation of chemical effects on the environment can provide an applied context to results, ideally a methodology of relevance to regulatory frameworks should be used. An approach adapting how SSDs are currently used in regulation to address assemblage sensitivity is pragmatic and accounts for any number of species exhibiting different chemical sensitivities (EFSA, 2013).

Use of a conventional SSD approach requires a single sensitivity value for each taxon to be calculated. The hSSD model was therefore used to generate EC_{50} values for all untested species in the total species pool and the average predicted EC_{50} value for each taxon was calculated from a geometric mean of 10,000 model runs. For each model run, the EC_{50} value (y) of species j to chemical i was calculated using Equation 1, where α_i is the 'true' sensitivity of species j, which is derived from the available toxicity data. The tendency of species j to be on average more or less sensitive to chemicals is given by β_j and $\varphi_i \delta_{ij}$ describes the interaction between chemical i and species j, including scaling for the variation of sensitivity for chemical i. The factor ε_{ijk} accounts for inter-test variation for toxicity testing.

$$y_{ijk} = \alpha_i + \beta_j + \varphi_i \delta_{ij} + \varepsilon_{ijk}. \tag{1}$$

Taxonomy is incorporated into the EC_{50} predictions through the sensitivity tendency of species (β_j) and the chemical-species interaction (δ_{ij}) by calculating individual values for these parameters for each taxonomic rank incorporated into the hSSD model. These ranks are species, genus, family, class, superclass, sub-phylum, phylum, kingdom and are numbered 1 to 9 in Equations 2a and 2b.

$$\beta_j = \beta_{1\,(j)} + \beta_{2\,(j)} + \ldots + \beta_{9(j)}, \tag{2a}$$

$$\delta_{ij} = \delta_{1\,(ij)} + \delta_{2\,(ij)} + \ldots + \delta_{9(ij)}. \tag{2b}$$

Model version 122b uses all taxonomic ranks except for sub-phylum and superclass. A detailed description of the hSSD model is described in Supporting Information S2. When running the hSSD model, the MCMC run had a burn in of 2500 MCMC time-steps per chemical and the predicted sensitivity values were calculated from 10,000 steps post-burn.

The predicted toxicity values were allocated to the 3040 study assemblages based on their taxonomic composition, resulting in five empirical SSDs per site (i.e., $SSD_{baseline}$ and four SSD_{future}). For each assemblage, the mean and standard deviation of the log-toxicities were determined and used to calculate a summary measure of the sensitivity of the assemblage. This choice of summary measure corresponds numerically to estimating the concentration hazardous to 5% of species (HC_5) based on fitting a log-normal SSD to toxicity data without enumerating the species to be protected or considering their taxonomy as in Wagner and Løkke (1991). Further information on how HC_5 and PAF are defined in the context of this paper is provided in the Supporting Information (S4).

The potentially affected fraction (PAF) of the baseline assemblage at the $HC_{5,\text{baseline}}$ is 5%, therefore deviations from a PAF of 5% for future assemblages (PAF_{future}) exposed to the $HC_{5,\text{baseline}}$ is a measure of site-specific change in assemblage sensitivity under future climate scenarios. The PAF_{future} for an assemblage and future climate scenario therefore measures the decrease (<5%) or increase (>5%) in sensitivity for the future climate scenario relative to baseline. Aggregating across the assemblages for each chemical, the mean ratio was calculated for each future climate scenario and the percentage of chemicals with an average increase or decrease in assemblage sensitivity was compared for the different climate scenarios.

3 | RESULTS

3.1 | Community composition

A total of 229 macroinvertebrate taxa were predicted to occur across the 608 study sites; 75% of which were arthropods, 12% molluscs, 11% annelids and 2% platyhelminthes. The Jaccard similarity for individual sites ranged from 7% to 100% between baseline (1981–2000) and future (2080–2099) scenarios, but on average decreased with increasing temperature change. By the end of the 21st century, assemblages at sites experiencing a 1.28°C temperature increase (i.e., RCP 2.6) had an average Jaccard similarity to their baseline assemblage of 65% (SE = 0.6%). Corresponding Jaccard similarity values for the other warming scenarios were 53% (SE = 0.7%) for RCP 4.5 (2.32°C increase), 49% (SE = 0.7%) for RCP 6.0 (2.70°C increase) and 40% (SE = 0.7%) for RCP 8.5 (i.e., 3.78°C increase).

The similarity in assemblage composition across all sites and scenarios is visualised in Figure 2. By the end of the century there was a significant difference in the composition of assemblages compared to their baseline for all four scenarios (PERMANOVA; $p < .01$). Mollusca and Malacostraca (Crustacea) and Oligochaeta had a large positive effect on the separation of assemblages along NMDS1, but Insecta orders had a range of responses including differences within the same order (Figure 2b).

Future warming drives a greater number of sites to have increasingly positive NMDS1 scores (Figure 2a), an effect that strengthens under increasing warming. Consequently, there is a broad gain of Mollusca, Malacostraca and Oligochaeta (Figure 3). In addition, some Insecta, namely Odonata, Chironomidae (Diptera) and Baetidae (Ephemeroptera) also become more common under warming.

Warming also causes a decrease in the number of sites with positive NMDS2 values (Figure 2a). Plecoptera, Ephemeroptera (except for Baetidae) and Coleoptera were predominantly associated with positive NMDS2 scores and there was a net decrease in these taxa, compared to baseline, with increasing warming (Figure 3).

3.2 | Effects on sensitivity

Predicted changes in the composition of invertebrate assemblages under climate change were associated with changes in the sensitivity of assemblages to chemical toxicants. For 15 of the 19 chemicals, the average sensitivity of assemblages to chemical exposure increased (i.e., PAF_{future} >5%) by the end of the century for all four climate scenarios. For a further three chemicals, average sensitivity increased under all climate scenarios except RCP2.6. For 1 of the 19 chemicals studied (carbaryl), assemblages on average became less sensitive under all four climate scenarios (Table 1). A full breakdown of the PAF_{future} values for each chemical-scenario combination is presented in Table S4.

PAF_{future} for assemblages exposed to their corresponding $HC_{5,\text{baseline}}$ are presented in Figure 4 for all chemicals. As the temperature of the scenario increased, the variation in PAF_{future} also increased (CV: 55.7 for $PAF_{\text{future,RCP2.6}}$ to 62.0 for $PAF_{\text{future,RCP8.5}}$), but in all cases, the dominant effect was an increase in sensitivity. The PAF_{future} increased from 5% ($HC_{5,\text{baseline}}$) to a maximum of between 32.0% ($PAF_{\text{future,RCP2.6}}$) and 44.7% at ($PAF_{\text{future,RCP8.5}}$) by the end of the century (i.e., 6.4- to 8.9-fold increase). For RCP2.6, warming resulted in 6.5% of assemblages (i.e., 749) doubling the percentage of species at risk (PAF_{future} >10%). Whereas for RCP8.5, warming resulted in 17.1% of assemblages (i.e., 1972) doubling the percentage of species at risk and 3.7% of assemblages (i.e., 437) quadrupling the percentage of species at risk (PAF_{future} >20%).

Figure 5 shows a clear split in the change to sensitivity along the cumulative frequency plots between the insecticides and the other chemicals. Although most assemblages exposed to insecticides become more sensitive under future conditions, they retain the steep cumulative frequency curve. In contrast the other chemicals, of which metals represent five of the six chemicals, have a much shallower cumulative frequency curve that is additionally associated with a greater increase in future assemblage sensitivity. Consequently, the non-insecticide chemicals investigated exhibit both a higher proportion of sensitive chemicals under future conditions and a greater number of assemblages experiencing high PAF_{future} values such as a doubling or quadrupling compared to the baseline. Furthermore, higher temperature increases were associated with increasing proportions of assemblages exhibiting these increases to PAF_{future}.

4 | DISCUSSION

Climate change and pollution are major drivers of biodiversity loss (IPBES et al., 2019), but they are not independent. Climate warming is known to increase the toxicity of chemical pollutants to individual species (Moe et al., 2013; Verheyen et al., 2022). However, less is

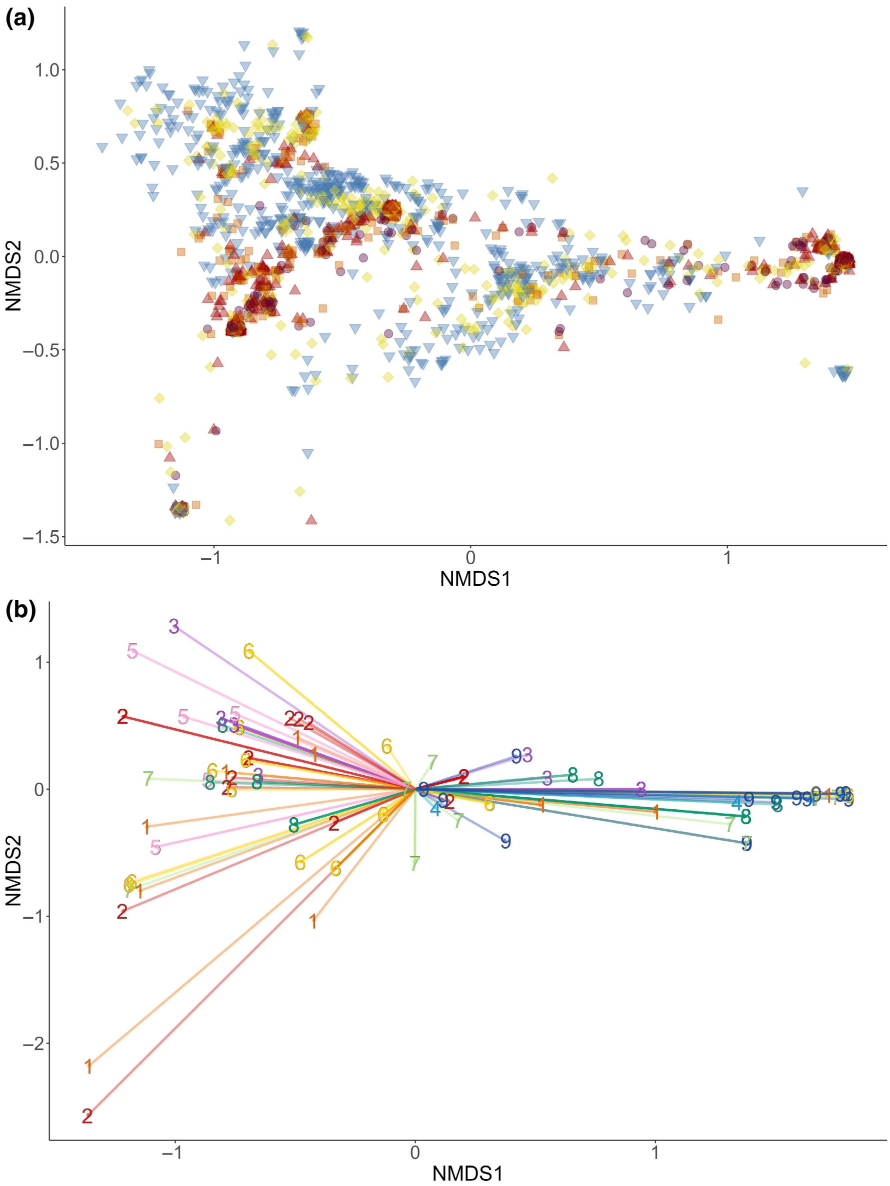

FIGURE 2 (a) Non-metric multidimensional scaling (NMDS) plot for the 3040 assemblages predicted for baseline and four future scenarios (each 608 assemblages). Each scenario is represented by a colour shape combination, with baseline being an inverted blue triangle, representative concentration pathway (RCP) 2.6 being a yellow diamond, RCP 4.5 an orange square, RCP 6.0 a red triangle and RCP 8.5 a dark red circle. (b) Plot displaying the average NMDS scores for macroinvertebrate taxonomic groups at the order level for arthropoda; Coleoptera (1, orange), Diptera (2, red), Ephemeroptera (3, purple), Malacostraca (4, light blue, i.e., Crustacea), Plecoptera (5, pink), Trichoptera (6, yellow), Other Arthropoda orders (7, light green) or phylum level for Annelida (8, dark green) and Mollusca (9, dark blue).

known about how climate-induced changes in biodiversity may alter the sensitivity of assemblages to chemical stress. By applying end of 21st century climate projections, we have demonstrated that the shift in the composition of river macroinvertebrate assemblages caused by climate warming across all scenarios resulted in over 70% of future assemblages becoming more sensitive to chemical toxicants. Almost 10% of assemblages exhibited a doubling in the number of species at risk from chemical exposure and 1% of assemblages exhibited a four-fold increase in risk to invertebrate biodiversity. Warming of ≥2.32°C was associated with an increase in the average sensitivity of assemblages to all bar one of the 19 chemicals investigated.

The four climate scenarios investigated represented a range of credible future pathways, with a projected temperature increase of 1.28°C (RCP 2.6) to 3.78°C (RCP 8.5), between 1981–2000 (baseline) and 2080–2100 (end of the century) (Lowe et al., 2018). The 608 study assemblages were distributed across the UK and were all minimally impacted by environmental stressors (Davy-Bowker et al., 2006). Predicted changes in the composition of macroinvertebrate assemblages became more pronounced with increased warming. At 3.78°C warming, the predicted similarity in species composition of baseline and end of the century assemblages was 40%. There is evidence that European riverine macroinvertebrate assemblages are already responding to decades of climate warming. Increases in insect species richness and decreases in macroinvertebrate abundances have been reported for streams exposed to around a 2°C rise in temperature over between 25 and 42 years (Baranov et al., 2020; Durance & Ormerod, 2007). Climate effects may not be observed at all sites due to confounding factors such as changes in land-use and water quality (Vaughan & Gotelli, 2019; Vaughan & Ormerod, 2014). However, as water quality improves (Pharaoh et al., 2023; Whelan et al., 2022), the effects of climate change on biodiversity may become more pronounced. Bioclimatic envelope modelling, for example, has demonstrated that >4.4°C

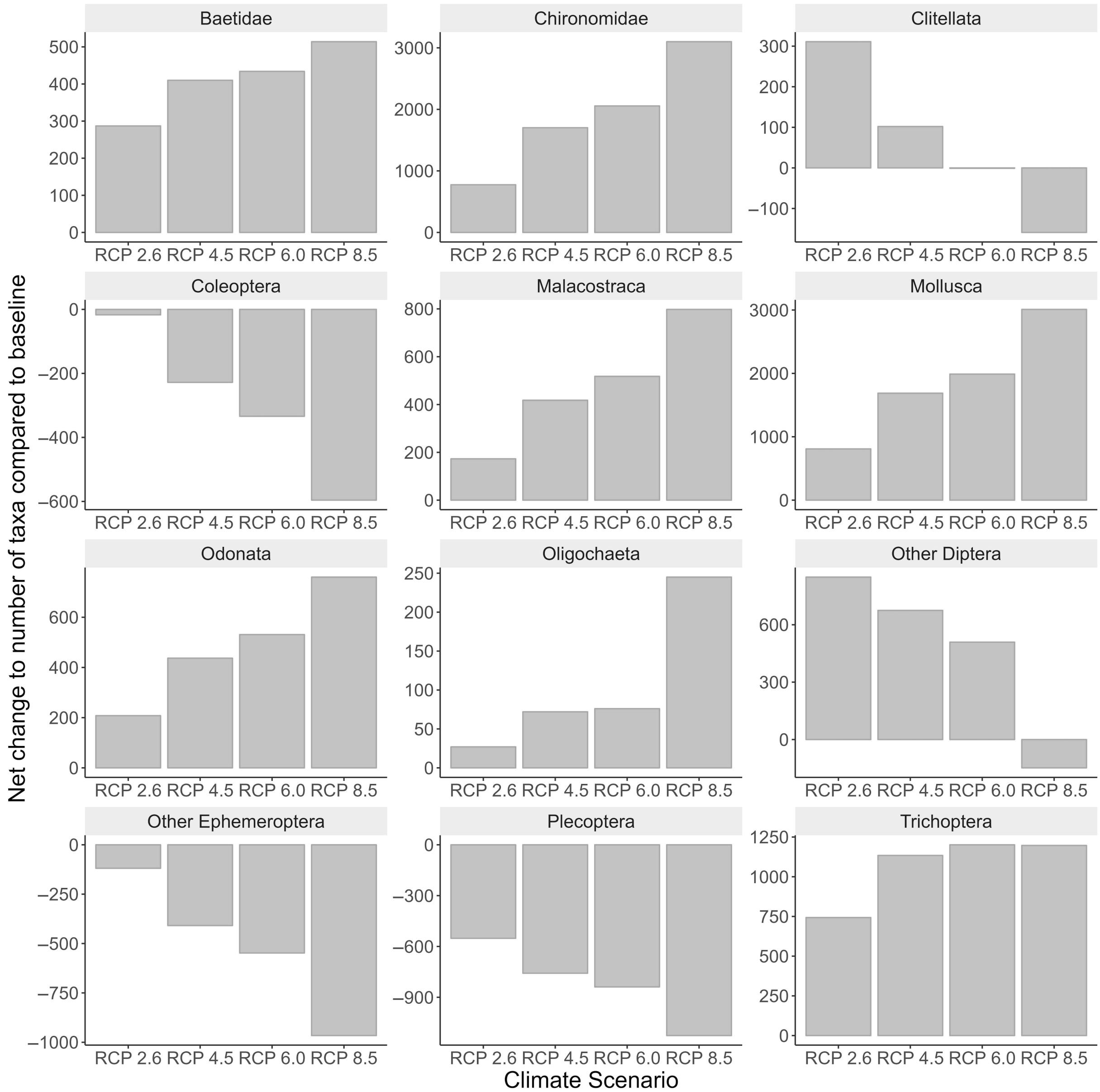

FIGURE 3 Net change in number of taxa present across 608 sites under each future warming scenario when compared to the taxa present within the baseline scenario. The net change in taxa has been separated to the patterns across 12 taxonomic groups. For the Insecta orders of Diptera and Ephemeroptera, the dominant families of Chironomidae and Baetidae respectively have been separated. This is because both families have multiple genera and exhibit different patterns under warming to their parent orders. Additionally, Annelida have been split into Oligochaeta and Clitellata due to the different responses to net change from warming. RCP, representative concentration pathways.

TABLE 1 Chemicals grouped according to whether, by the end of the century (2080–2100), the average sensitivity of assemblages to a chemical had increased (PAF_{future} >0.05) or decreased when (PAF_{future} <0.05) compared with their baseline (1980–2000). The three groups were: PAF_{future} <0.05 for all future scenarios (Consistently less sensitive), PAF_{future} >0.05 for most future scenarios (Predominantly more sensitive), PAF_{future} >0.05 in all four scenarios (Consistently more sensitive). The exact magnitude of change for each chemical is given in Table S4.

Consistently less sensitivity	Predominantly more sensitivity	Consistently more sensitivity
Carbaryl	Endosulfan, Lindane, Lead	DDT, Carbofuran, Diazinon Fenitrothion, Malathion Parathion-methyl, Azinphos-methyl, Parathion-ethyl Methoxychlor, Deltamethrin Pentachlorophenol, Copper, Zinc, Nickel, Cadmium

Abbreviation: PAF, potentially affected fraction.

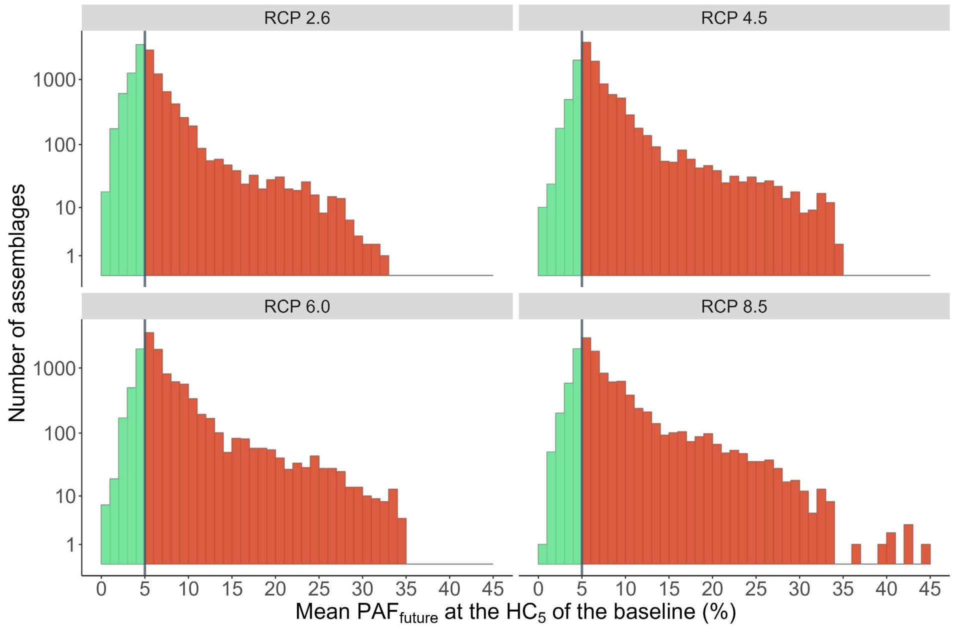

FIGURE 4 Distribution of predicted PAF$_{future}$ values for 608 assemblages when exposed to each of the 19 chemicals individually under each of the future scenarios (i.e., 10,336 assemblages per future scenario). Red indicates a predicted increase in sensitivity (PAF$_{future}$ >5%) and green represents a predicted decrease in sensitivity (PAF$_{future}$ <5%) compared with the baseline. A logarithmic base 10 scale is used on the y-axis representing the number of assemblages. PAF, potentially affected fraction; RCP, representative concentration pathways.

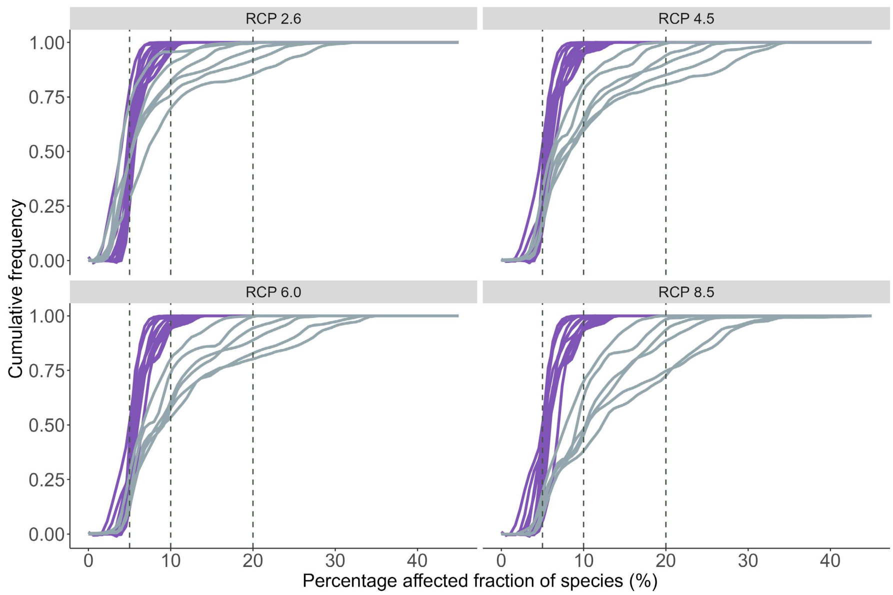

FIGURE 5 Predicted PAF$_{future}$ cumulative frequency curves for the 608 assemblages when individually exposed to 19 chemicals under each of the four climate scenarios. A curve represents a single chemical and is colour-coded into insecticides (purple) and other chemicals (grey). Dashed vertical lines indicate PAF$_{future}$ values of 5%, 10%, and 20%, that is hazard concentrations for 5%, 10% and 20% of taxa, respectively. PAF, potentially affected fraction; RCP, representative concentration pathways.

warming would reduce the climatically suitable area for >57% of European stream macroinvertebrates by 2080, although climatically suitable conditions would persist in Europe for 99% of the species modelled (Domisch et al., 2013).

Climate warming was predicted to favour specific taxonomic groups. A projected warming of >1.28°C was associated with end of the century assemblages that either had: (i) increased occurrence of Mollusca, Crustacea and Oligochaeta, but generally fewer insect groups than baseline; or (ii) increased occurrence of Odonata, Chironomidae (Diptera) and Baetidae (Ephemeroptera) insect species, but fewer Plecoptera and Ephemeroptera (except for Baetidae) and Coleoptera species than baseline. These shifts in community composition are explicable, in part, in terms of taxonomic differences in thermal tolerances (Macadam et al., 2022). Plecoptera and Ephemeroptera have lower upper thermal tolerances than other taxa, especially Mollusca (Stewart et al., 2013). While in general, Coleoptera have a high mean upper thermal tolerance, but Elmidae, which are common Coleoptera in well-aerated streams and rivers, have been identified as being potentially vulnerable to elevated water temperature (Elliott, 2008). Similar shifts in the thermal trait profiles of macroinvertebrate assemblages have been associated with long-term exposure (30–42 years) to small temperature increases (0.9–1.5°C) in European rivers (Chessman, 2012; Floury et al., 2017).

This study used a novel approach to predict the chemical sensitivity of macroinvertebrate assemblages. The use of the hSSD model-enabled chemical-specific toxicity endpoints (EC_{50} values) to be generated for untested species and hence the quantification of assemblage-specific sensitivities, defined as the HC_5. By combining the predictions of future assemblage composition with the hSSD model, it was possible to quantify the risk that the 19 individual study chemicals posed to species in each of the 608 assemblages under the four climate scenarios. Across all chemicals and scenarios, the chemical sensitivity of 70.6% assemblages was predicted to be higher at the end of the century compared with baseline. For individual climate scenarios, chemical sensitivity was predicted to increase for 56.8% of assemblages under the lowest emissions pathway (RCP 2.6, 1.28°C increase) and for 75.7% of assemblages under the high emissions scenario (RCP 8.5, 3.78°C increase).

However, the patterns and magnitude of change in sensitivity varied by chemical and was most pronounced for the metals copper, zinc, nickel and cadmium. More than half the assemblages exposed to these metals under a 3.78°C warming would have at least a doubling of the number of species potentially at risk posing a significant threat to biodiversity. For individual assemblages, the increased risk can be more extreme. For instance, a warming of 3.78°C was predicted to increase the percentage of species at risk from cadmium from 5% to 45%. Copper, zinc, nickel and cadmium are listed in the top 10 chemicals of concern in British rivers (Johnson et al., 2017) and therefore the combined impact of climate change and metal pollution may be particularly detrimental to UK freshwater biodiversity.

While these results highlight metals as being potentially problematic in a warming world, insecticides and the general biocide pentachlorophenol also exhibited consistent and large increases in sensitivity under climate warming. Increasing temperatures shifted assemblage composition either towards soft bodied taxa such as Mollusca and Oligochaeta, which are known to be sensitive to metals (Bjerregaard et al., 2015; Brix et al., 2005; Verschoor et al., 2011), or towards specific Arthropoda groups such as Crustacea, Odonata, Chironomidae and Baetidae (Figure 3). However, it should be noted that these patterns are not necessarily indicative of a direct mechanism linking temperature and the sensitivity of species to chemical contaminants. Rather, chemical sensitivity varies amongst species and the relative sensitivity of species varies between chemicals (Craig et al., 2012; Raimondo et al., 2008). Consequently, the favouring of a specific species under warming could theoretically either increase or decrease assemblage sensitivity depending on the shift in assemblage composition and hence the species sensitivity profile for the specific assemblage and chemical.

The 19 chemicals used in this study were selected from an initial list of 38 chemicals, based on the richness and taxonomic diversity of their toxicity data set and their fit to the hSSD model (Table S3). The selected chemicals included examples of the major specific modes of toxic action: acetylcholinesterase inhibition (organophosphate and carbamate mediated), neurotoxicity (diphenyl and pyrethroid sodium channel modulation, alicyclic GABA antagonism), electron transport inhibition (uncoupling of oxidative phosphorylation) and iono/osmoregulatory impairment (Barron et al., 2015). The mode of toxic action included in the original 38 chemicals but absent from the final 19 is narcosis (Table S3). This chemical selection highlights the limited taxonomic richness and diversity of laboratory toxicity data for many chemicals, especially those with a narcotic toxic mode of action, an observation which has been made previously (e.g., Barron et al., 2013).

Climate-induced changes in the composition and hence chemical sensitivity of freshwater assemblages may be exacerbated by the synergistic effects of temperature on chemical toxicity (Hooper et al., 2013; Polazzo et al., 2022; Raths et al., 2023) and by the increase in chemical exposure due to changes to precipitation patterns (Biswas et al., 2018) or chemical use (Martínez-Megías et al., 2023). Climate change may also influence other factors that determine the distribution of freshwater species including flow regime and substrate composition (O'Briain, 2019). However, even in the absence of these additional factors, the impact of chemical stressors on biodiversity will become more pronounced in a warming world and current assessments of risks to biodiversity from chemicals may be underprotective. There is therefore a need for environmental risk assessment procedures to consider the interactions between climate change and chemical exposure in order to adequately protect current and future biodiversity.

The combination of spatially-explicit climate predictions coupled with models to predict changes in species distributions (e.g., bioclimatic or RICT-type models) and sensitivity profiles (e.g., hSSD model) provides a useful and novel approach for predicting chemical risk to natural assemblages, highlighting areas for biodiversity protection and pre-empting necessary action from future effects of climate change (Camargo, 1994; Vernier et al., 2017). However, as with other approaches to predict future assemblages, these models are not without limitations or uncertainties (Heikkinen et al., 2006). RICT is a reference-based system that captures the suite of environmental and ecological factors representative of sites across the UK. This includes a range in average temperatures from 7.93 to 11.45°C. Warming resulting from climate change will increasingly push the model beyond its domain, particularly for sites in southern England. In addition, while some invasive species are considered in RICT they may not reflect the range of species that might invade the UK over the 21st century. Reassuringly, the shifts towards more Mollusca, Malacostraca and Odonata taxa under climate warming projected in this study are consistent with existing monitoring studies (Durance & Ormerod, 2007; Vaughan & Ormerod, 2014).

The advantage of the hSSD model over existing SSD approaches is that it provides the option to move away from a generic assessment of risk (Posthuma et al., 2019; Raimondo et al., 2008) to an assessment that considers the species composition of the community being exposed. In common with all SSD approaches, the hSSD model does not account for species interactions (Brose et al., 2019; Kidd et al., 2014), which may also be affected by climate change (Woodward et al., 2010). However, the hSSD method does provide increased realism compared to the standard SSD approach by considering the sensitivity of all naturally occurring taxa and reflecting variation in taxonomic composition between sites.

In summary, the projected thermal effects of climate change on UK rivers resulted in shifts in macroinvertebrate assemblages either towards increasing Mollusca, Crustacea and Oligochaetea species or towards increasing Odonata, Chironomidae and Baetidae species, with a decrease in Plecoptera, Ephemeroptera and Coleoptera species. The sensitivity of most assemblages to toxic chemicals increased under climate warming and this was particularly marked for metals. Climate change has the potential to affect the use (Rasche, 2021), fate and environmental concentration (Biswas et al., 2018) and toxicity (Macaulay et al., 2021) of chemicals with implications for biodiversity and freshwater ecosystems (EFSA et al., 2020). However, this study has demonstrated that, even in the absence of such climate–chemical interactions, the impact of chemical pollution on freshwater biodiversity may double or quadruple by the end of the 21st century due to climate warming-induced changes in species composition.

AUTHOR CONTRIBUTIONS

Tom Sinclair: Conceptualization; data curation; formal analysis; investigation; methodology; software; validation; visualization; writing – original draft; writing – review and editing. **Peter Craig:** Software; writing – review and editing. **Lorraine L. Maltby:** Conceptualization; investigation; methodology; supervision; writing – original draft; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data and code that support the findings of this study are openly available in Dryad at https://doi.org/10.5061/dryad.zs7h44jhb.

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REFERENCES

Armitage, P. D. (2000). *The potential of RIVPACS for predicting the effects of environmental change*. Freshwater Biological Association.

Arnell, N. W., Kay, A. L., Freeman, A., Rudd, A. C., & Lowe, J. A. (2021). Changing climate risk in the UK: A multi-sectoral analysis using policy-relevant indicators. *Climate Risk Management*, *31*(100), 265. https://doi.org/10.1016/j.crm.2020.100265

Baranov, V., Jourdan, J., Pilotto, F., Wagner, R., & Haase, P. (2020). Complex and nonlinear climate-driven changes in freshwater insect communities over 42 years. *Conservation Biology*, *34*(5), 1241–1251. https://doi.org/10.1111/cobi.13477

Barbarossa, V., Bosmans, J., Wanders, N., King, H., Bierkens, M. F. P., Huijbregts, M. A. J., & Schipper, A. M. (2021). Threats of global warming to the world's freshwater fishes. *Nature Communications*, *12*(1), 1701. https://doi.org/10.1038/s41467-021-21,655-w

Barron, M. G., Hemmer, M. J., & Jackson, C. R. (2013). Development of aquatic toxicity benchmarks for oil products using species sensitivity distributions. *Integrated Environmental Assessment and Management*, *9*(4), 610–615. https://doi.org/10.1002/ieam.1420

Barron, M. G., Lilavois, C. R., & Martin, T. M. (2015). MOAtox: A comprehensive mode of action and acute aquatic toxicity database for predictive model development. *Aquatic Toxicology*, *161*, 102–107. https://doi.org/10.1016/j.aquatox.2015.02.001

Berger, E., Haase, P., Kümmerlen, M., Leps, M., Schäfer, R. B., & Sundermann, A. (2017). Water quality variables and pollution sources shaping stream macroinvertebrate communities. *Science of the Total Environment*, *587–588*(June), 1–10. https://doi.org/10.1016/j.scitotenv.2017.02.031

Birk, S., Chapman, D., Carvalho, L., Spears, B. M., Andersen, H. E., Argillier, C., & Auer, S. (2020). Impacts of multiple stressors on freshwater biota across spatial scales and ecosystems. *Nature Ecology & Evolution*, *4*(8), 1060–1068. https://doi.org/10.1038/s41559-020-1216-4

Biswas, B., Qi, F., Biswas, J. K., Wijayawardena, A., Khan, M. A. I., & Naidu, R. (2018). The fate of chemical pollutants with soil properties and processes in the climate change paradigm—A review. *Soil Systems*, *2*(3), 51. https://doi.org/10.3390/soilsystems2030051

Bjerregaard, P., Andersen, C. B. I., & Andersen, O. (2015). Chapter 21—Ecotoxicology of metals—Sources, transport, and effects on the ecosystem. In G. F. Nordberg, B. A. Fowler, & M. Nordberg (Eds.), *Handbook on the toxicology of metals* (4th ed., pp. 425–459). Academic Press. https://doi.org/10.1016/B978-0-444-59,453-2.00021-4

Brix, K. V., DeForest, D. K., Burger, M., & Adams, W. J. (2005). Assessing the relative sensitivity of aquatic organisms to divalent metals and their representation in toxicity datasets compared to natural aquatic communities. *Human and Ecological Risk Assessment*, *11*(6), 1139–1156. https://doi.org/10.1080/10807030500278628

Brose, U., Archambault, P., Barnes, A. D., Bersier, L., Boy, T., Canning-Clode, J., Conti, E., Dias, M., Digel, C., & Dissanayake, A. (2019). Predator traits determine food-web architecture across ecosystems. *Nature Ecology & Evolution*, *3*(6), 919–927. https://doi.org/10.1038/s41559-019-0899-x

Cabral, H., Fonseca, V., Sousa, T., & Costa Leal, M. (2019). Synergistic effects of climate change and marine pollution: An overlooked interaction in coastal and estuarine areas. *International Journal of Environmental Research and Public Health*, *16*(15), 2737. https://doi.org/10.3390/ijerph16152737

Cairns, J., Lanza, G. R., & Parker, B. C. (1972). Pollution related structural and functional changes in aquatic communities with emphasis on freshwater algae and protozoa. *Proceedings of the Academy of Natural Sciences of Philadelphia*, *124*, 79–127.

Camargo, J. A. (1994). The importance of biological monitoring for the ecological risk assessment of freshwater pollution: A case study. *Environment International*, *20*(2), 229–238. https://doi.org/10.1016/0160-4120(94)90140-6

Chamberlain, S. A., & Szöcs, E. (2013). Taxize: Taxonomic search and retrieval in R [version 2; peer review: 3 approved]. *F1000Research*, *2*, 191. https://doi.org/10.12688/f1000research.2-191.v2

Chessman, B. C. (2012). Biological traits predict shifts in geographical ranges of freshwater invertebrates during climatic warming and drying. *Journal of Biogeography*, *39*, 957–969. https://doi.org/10.1111/j.1365-2699.2011.02647.x

Clarke, R. T., Wright, J. F., & Furse, M. T. (2003). RIVPACS models for predicting the expected macroinvertebrate fauna and assessing the ecological quality of rivers. *Ecological Modelling*, *160*(3), 219–233. https://doi.org/10.1016/S0304-3800(02)00255-7

Cox, R., Wright, J. F., Furse, M. T., & Moss, D. (1997). *RIVPACS III-Great Britain user manual*. Institute of Freshwater Ecology.

Craig, P. S. (2013). *Exploring novel ways of using species sensitivity distributions to establish PNECs for industrial chemicals: Final report to project steering group 3 April 2013*. Technical report. http://dro.dur.ac.uk/13383/

Craig, P. S., Hickey, G. L., Luttik, R., & Hart, A. (2012). Species non-exchangeability in probabilistic ecotoxicological risk assessment. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *175*(1), 243–262. https://doi.org/10.1111/j.1467-985X.2011.00716.x

Davy-Bowker, J., Clarke, R. T., Corbin, T. A., Vincent, H. M., Pretty, J., Hawczak, A., Murphy, J. F., & Jones, I. (2008). *SNIFFER WFD72C final report on River Invertebrate Classification Tool*. SNIFFER.

Davy-Bowker, J., Clarke, R. T., Johnson, R. K., Kokes, J., Murphy, J. F., & Zahrádková, S. (2006). A comparison of the European water framework directive physical typology and RIVPACS-type models as alternative methods of establishing reference conditions for benthic macroinvertebrates. *Hydrobiologia*, *566*(1), 91–105. https://doi.org/10.1007/s10750-006-0068-5

Domisch, S., Araujo, M. B., Bonada, N., Pauls, S. U., Jaenig, S. C., & Haase, P. (2013). Modelling distribution in European stream macroinvertebrates under future climates. *Global Change Biology*, *19*(3), 752–762. https://doi.org/10.1111/gcb.12107

Dudgeon, D., Arthington, A. H., Gessner, M. O., Kawabata, Z., Knowler, D. J., Leveque, C., & Naiman, R. J. (2006). Freshwater biodiversity: Importance, threats, status and conservation challenges. *Biological Reviews*, *81*, 163–182. https://doi.org/10.1017/S1464793105006950

Durance, I., & Ormerod, S. J. (2007). Climate change effects on upland stream macroinvertebrates over a 25-year period. *Global Change Biology*, *13*, 942–957. https://doi.org/10.1111/j.1365-2486.2007.01340.x

EFSA. (2013). Guidance on tiered risk assessment for plant protection products for aquatic organisms in edge-of-field surface waters. *EFSA Journal*, *11*(7), 3290. https://doi.org/10.2903/j.efsa.2013.3290

EFSA, Maggiore, A., Afonso, A., Barrucci, F., & De Sanctis, G. (2020). Climate change as a driver of emerging risks for food and feed safety, plant, animal health and nutritional quality. *EFSA Supporting Publications*, *17*(6), 1881E. https://doi.org/10.2903/sp.efsa.2020.EN-1881

Elliott, M. J. (2008). The ecology of riffle beetles (Coleoptera: Elmidae). *Freshwater Reviews*, *1*(2), 189–203. https://doi.org/10.1608/FRJ-1.2.4

Environment Agency (EA), NIEA, NRW, and SEPA. (2021). *River Invertebrate Classification Tool (RICT)*. Freshwater Biology Association. https://www.fba.org.uk/FBA/Public/Discover-and-Learn/Projects/RIVPACS_Landing.aspx

Floury, M., Usseglio-Polatera, P., Delattre, C., & Souchon, Y. (2017). Assessing long-term effects of multiple, potentially confounded drivers in ecosystems from species traits. *Global Change Biology*, *23*(6), 2297–2307. https://doi.org/10.1111/gcb.13575

Gessner, M. O., & Tlili, A. (2016). Fostering integration of freshwater ecology with ecotoxicology. *Freshwater Biology*, *61*(12), 1991–2001. https://doi.org/10.1111/fwb.12852

Grizzetti, B., Liquete, C., Pistocchi, A., Vigiak, O., Zulian, G., Bouraoui, F., De Roo, A., & Cardoso, A. C. (2019). Relationship between ecological condition and ecosystem services in European rivers, lakes and coastal waters. *Science of the Total Environment*, *671*(June), 452–465. https://doi.org/10.1016/j.scitotenv.2019.03.155

Guenard, G., von der Ohe, P. C., Walker, S. C., Lek, S., & Legendre, P. (2014). Using phylogenetic information and chemical properties to predict species tolerances to pesticides. *Proceedings of the Royal Society B: Biological Sciences*, *281*(1789), 20133239. https://doi.org/10.1098/rspb.2013.3239

Heikkinen, R. K., Luoto, M., Araújo, M. B., Virkkala, R., Thuiller, W., & Sykes, M. T. (2006). Methods and uncertainties in bioclimatic envelope modelling under climate change. *Progress in Physical Geography*, *30*(6), 751–777. https://doi.org/10.1177/0309133306071957

Hooper, M. J., Ankley, G. T., Cristol, D. A., Maryoung, L. A., Noyes, P. D., & Pinkerton, K. E. (2013). Interactions between chemical and climate stressors: A role for mechanistic toxicology in assessing climate change risks. *Environmental Toxicology and Chemistry*, *32*(1), 32–48. https://doi.org/10.1002/etc.2043

IPBES, Brondizio, E. S., Settele, J., Díaz, S., & Ngo, H. T. (2019). *Global assessment report on biodiversity and ecosystem Services of the intergovernmental science-policy platform on biodiversity and ecosystem services* (Vol. *56*). IPBES Secretariat. https://doi.org/10.5281/zenodo.3553579

IPCC. (2022). Summary for policymakers: Climate change 2022: Impacts, adaptation, and vulnerability. In H. O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, & A. Okem (Eds.), *Contribution of working group II to the sixth assessment report of the Intergovernmental Panel on Climate Change* (pp. 1–33). Cambridge University Press.

Ippolito, A., Todeschini, R., & Vighi, M. (2012). Sensitivity assessment of freshwater macroinvertebrates to pesticides using biological traits. *Ecotoxicology*, *21*(2), 336–352. https://doi.org/10.1007/s10646-011-0795-x

Johnson, A. C., Donnachie, R. L., Sumpter, J. P., Jürgens, M. D., Moeckel, C., & Pereira, M. G. (2017). An alternative approach to risk rank chemicals on the threat they pose to the aquatic environment. *Science of the Total Environment*, *599*, 1372–1381.

Johnson, R. K., & Sandin, L. (2001). *Development of a prediction and classification system for lake (Littoral, SWEPAC [–] LLI) and Stream (Riffle SWEPAC [–] SRI) Macroinvertebrate Communities. Rapport 23*. Sveriges lantbruksuniv.

Kibria, G., Nugegoda, D., Rose, G., & Haroon, Y. A. K. (2021). Climate change impacts on pollutants mobilization and interactive effects of climate change and pollutants on toxicity and bioaccumulation of pollutants in estuarine and marine biota and linkage to seafood security. *Marine Pollution Bulletin*, *167*(June), 112364. https://doi.org/10.1016/j.marpolbul.2021.112364

Kidd, K. A., Paterson, M. J., Rennie, M. D., Podemski, C. L., Findlay, D. L., Blanchfield, P. J., & Liber, K. (2014). Direct and indirect responses of a freshwater food web to a potent synthetic Oestrogen. *Philosophical Transactions of the Royal Society, B: Biological Sciences*, *369*(1656), 20130578. https://doi.org/10.1098/rstb.2013.0578

LaLone, C. A., Villeneuve, D. L., Burgoon, L. D., Russom, C. L., Helgen, H. W., Berninger, J. P., Tietge, J. E., Severson, M. N., Cavallin, J. E., & Ankley, G. T. (2013). Molecular target sequence similarity as a basis for species extrapolation to assess the ecological risk of chemicals with known modes of action. *Aquatic Toxicology*, *144–145*(November), 141–154. https://doi.org/10.1016/j.aquatox.2013.09.004

Lowe, J. A., Bernie, D., Bett, P., Bricheno, L., Brown, S., Calvert, D., Clark, R., Eagle, K., Edwards, T., & Fosser, G. (2018). *UKCP18 science overview report*. Met Office Hadley Centre.

Macadam, C. R., England, J., & Chadd, R. (2022). The vulnerability of British aquatic insects to climate change. *Knowledge and*

Management of Aquatic Ecosystems, *423*, 3. https://doi.org/10.1051/kmae/2022003

Macaulay, S. J., Hageman, K. J., Piggott, J. J., & Matthaei, C. D. (2021). Time-cumulative effects of neonicotinoid exposure, heatwaves and food limitation on stream mayfly nymphs: A multiple-stressor experiment. *Science of the Total Environment*, *754*(131), 941. https://doi.org/10.1016/j.scitotenv.2020.141941

Malaj, E., Guenard, G., Schäfer, R. B., & von der Ohe, P. C. (2016). Evolutionary patterns and physicochemical properties explain macroinvertebrate sensitivity to heavy metals. *Ecological Applications*, *26*(4), 1249–1259. https://doi.org/10.1890/15-0346

Maltby, L., Blake, N., Brock, T. C. M., & Van den Brink, P. J. (2005). Insecticide species sensitivity distributions: Importance of test species selection and relevance to aquatic ecosystems. *Environmental Toxicology and Chemistry*, *24*(2), 379–388. https://doi.org/10.1897/04-025R.1

Manjarrés, H., Cástor, A. G., & García Roselló, E. (2021). Predicting the effects of climate change on future freshwater fish diversity at global scale. *Nature Conservation*, *43*, 1–24. https://doi.org/10.3897/natureconservation.43.58997

Martínez-Megías, C., Mentzel, S., Fuentes-Edfuf, Y., Moe, S. J., & Rico, A. (2023). Influence of climate change and pesticide use practices on the ecological risks of pesticides in a protected Mediterranean wetland: A Bayesian network approach. *Science of the Total Environment*, *878*(June), 163018. https://doi.org/10.1016/j.scitotenv.2023.163018

Maxwell, S. L., Fuller, R. A., Brooks, T. M., & Watson, J. E. M. (2016). Biodiversity: The ravages of guns, nets and bulldozers. *Nature News*, *536*(7615), 143–145.

Met Office. (2019). *Met Office Hadley Centre (2019): UKCP local projections on a 5km grid over the UK for 1980–2080*. https://catalogue.ceda.ac.uk/uuid/e304987739e04cdc960598fa5e4439d0

Moe, J. S., De Schamphelaere, K., Clements, W. H., Sorensen, M. T., Van den Brink, P. J., & Liess, M. (2013). Combined and interactive effects of global climate change and toxicants on populations and communities. *Environmental Toxicology and Chemistry*, *32*(1), 49–61. https://doi.org/10.1002/etc.2045

O'Briain, R. (2019). Climate change and European rivers: An eco-hydromorphological perspective. *Ecohydrology*, *12*(5), e2099. https://doi.org/10.1002/eco.2099

Oksanen, J., Blanchet, F. G., Kindt, R., Legendre, P., Minchin, P. R., O'hara, R. B., Simpson, G. L., Solymos, P., Stevens, M. H., & Wagner, H. (2013). *Package "Vegan"*. Community Ecology Package, Version 2 (9): 1–295.

Olker, J. H., Elonen, C. M., Pilli, A., Anderson, A., Kinziger, B., Erickson, S., Skopinski, M., Pomplun, A., LaLone, C. A., & Russom, C. L. (2022). The ECOTOXicology knowledgebase: A curated database of ecologically relevant toxicity tests to support environmental research and risk assessment. *Environmental Toxicology and Chemistry*, *41*(6), 1520–1539. https://doi.org/10.1002/etc.5324

Op de Beeck, L., Verheyen, J., & Stoks, R. (2018). Strong differences between two congeneric species in sensitivity to pesticides in a warming world. *Science of the Total Environment*, *618*(March), 60–69. https://doi.org/10.1016/j.scitotenv.2017.10.311

Persson, L., Carney Almroth, B. M., Collins, C. D., Cornell, S., de Wit, C. A., Diamond, M. L., & Fantke, P. (2022). Outside the safe operating space of the planetary boundary for novel entities. *Environmental Science & Technology*, *56*(3), 1510–1521. https://doi.org/10.1021/acs.est.1c04158

Peters, A., Simpson, P., & Moccia, A. (2014). Accounting for both local aquatic community composition and bioavailability in setting site-specific quality standards for zinc. *Environmental Science and Pollution Research*, *21*, 105–117. https://doi.org/10.1007/s11356-013-1720-z

Pharaoh, E., Diamond, M., Ormerod, S. J., Rutt, G., & Vaughan, I. P. (2023). Evidence of biological recovery from gross pollution in English and Welsh rivers over three decades. *Science of the Total Environment*, *878*(June), 163107. https://doi.org/10.1016/j.scitotenv.2023.163107

Pinheiro, J. P. S., Windsor, F. M., Wilson, R. W., & Tyler, C. R. (2021). Global variation in freshwater physico-chemistry and its influence on chemical toxicity in aquatic wildlife. *Biological Reviews*, *96*(4), 1528–1546. https://doi.org/10.1111/brv.12711

Polazzo, F., Roth, S. K., Hermann, M., Mangold-Döring, A., Rico, A., Sobek, A., Van den Brink, P. J., & Jackson, M. C. (2022). Combined effects of heatwaves and micropollutants on freshwater ecosystems: Towards an integrated assessment of extreme events in multiple stressors research. *Global Change Biology*, *28*(4), 1248–1267. https://doi.org/10.1111/gcb.15971

Poquet, J. M., Alba-Tercedor, J., Puntí, T., del Mar Sánchez-Montoya, M., Robles, S., Alvarez, M., Zamora-Munoz, C., Sáinz-Cantero, C. E., Vidal-Abarca, M. R., & Suárez, M. L. (2009). The MEDiterranean Prediction and Classification System (MEDPACS): An implementation of the RIVPACS/AUSRIVAS predictive approach for assessing Mediterranean aquatic macroinvertebrate communities. *Hydrobiologia*, *623*, 153–171. https://doi.org/10.1007/s10750-008-9655-y

Posthuma, L., Suter, G. W., II, & Traas, T. P. (2001). *Species sensitivity distributions in ecotoxicology*. CRC Press.

Posthuma, L., van Gils, J., Zijp, M. C., van de Meent, D., & de Zwart, D. (2019). Species sensitivity distributions for use in environmental protection, assessment, and management of aquatic ecosystems for 12386 chemicals. *Environmental Toxicology and Chemistry*, *38*(4), 905–917. https://doi.org/10.1002/etc.4373

Raimondo, S., Vivian, D. N., Delos, C., & Barron, M. G. (2008). Protectiveness of species sensitivity distribution hazard concentrations for acute toxicity used in endangered species risk assessment. *Environmental Toxicology and Chemistry*, *27*(12), 2599–2607. https://doi.org/10.1897/08-157.1

Rasche, L. (2021). Estimating pesticide inputs and yield outputs of conventional and organic agricultural systems in Europe under climate change. *Agronomy*, *11*(7), 1300. https://doi.org/10.3390/agronomy11071300

Raths, J., Švara, V., Lauper, B., Fu, Q., & Hollender, J. (2023). Speed it up: How temperature drives toxicokinetics of organic contaminants in freshwater amphipods. *Global Change Biology*, *29*(5), 1390–1406. https://doi.org/10.1111/gcb.16542

Reid, A. J., Carlson, A. K., Creed, I. F., Eliason, E. J., Gell, P. A., Johnson, P. T. J., & Kidd, K. A. (2019). Emerging threats and persistent conservation challenges for freshwater biodiversity. *Biological Reviews*, *94*(3), 849–873. https://doi.org/10.1111/brv.12480

Rubach, M. N., Baird, D. J., & Van den Brink, P. J. (2010). A new method for ranking mode-specific sensitivity of freshwater arthropods to insecticides and its relationship to biological traits. *Environmental Toxicology and Chemistry*, *29*(2), 476–487. https://doi.org/10.1002/etc.55

Sánchez-Bayo, F., & Wyckhuys, K. A. G. (2019). Worldwide decline of the entomofauna: A review of its drivers. *Biological Conservation*, *232*(April), 8–27. https://doi.org/10.1016/j.biocon.2019.01.020

Schoch, C. L., Ciufo, S., Domrachev, M., Hotton, C. L., Kannan, S., Khovanskaya, R., & Leipe, D. (2020). NCBI taxonomy: A comprehensive update on curation resources and tools. *Database*. https://doi.org/10.1093/database/baaa062

Simpson, J. C., & Norris, R. H. (2000). Biological assessment of river quality: Development of AUSRIVAS models and outputs. In *Assessing the biological quality of fresh waters: RIVPACS and other techniques. Proceedings of an International Workshop Held in Oxford, UK, on 16–18 September 1997*, 125–142. Freshwater Biological Association (FBA).

Stewart, B. A., Close, P. G., Cook, P. A., & Davies, P. M. (2013). Upper thermal tolerances of key taxonomic groups of stream invertebrates. *Hydrobiologia*, *718*, 131–140. https://doi.org/10.1007/s10750-013-1611-9

UKTAG, WFD. (2008). *UK environmental standards and conditions (phase 1)*. Final reports. UK Technical Advisory Group on the Water Framework Directive (WFD UKTAG), 1–73.

Vaal, M. A., Van Leeuwen, C. J., Hoekstra, J. A., & Hermens, J. L. M. (2000). Variation in sensitivity of aquatic species to toxicants: Practical consequences for effect assessment of chemical substances. *Environmental Management*, *25*(4), 415–423. https://doi.org/10.1007/s002679910033

Van den Berg, S. J. P., Baveco, H., Butler, E., De Laender, F., Focks, A., Franco, A., Rendal, C., & Van den Brink, P. J. (2019). Modeling the sensitivity of aquatic macroinvertebrates to chemicals using traits. *Environmental Science & Technology*, *53*(10), 6025–6034. https://doi.org/10.1021/acs.est.9b00893

Van den Berg, S. J. P., Maltby, L., Sinclair, T., Liang, R., & van den Brink, P. J. (2021). Cross-species extrapolation of chemical sensitivity. *Science of the Total Environment*, *753*(141), 800. https://doi.org/10.1016/j.scitotenv.2020.141800

Van den Berg, S. J. P., Rendal, C., Focks, A., Butler, E., Peeters, E., De Laender, F., & Van den Brink, P. J. (2020). Potential impact of chemical stress on freshwater invertebrates: A sensitivity assessment on continental and national scale based on distribution patterns, biological traits, and relatedness. *Science of the Total Environment*, *731*, 139–150. https://doi.org/10.1016/j.scitotenv.2020.139150

Vaughan, I. P., & Gotelli, N. J. (2019). Water quality improvements offset the climatic debt for stream macroinvertebrates over twenty years. *Nature Communications*, *10*(1), 1956. https://doi.org/10.1038/s41467-019-09736-3

Vaughan, I. P., & Ormerod, S. J. (2014). Linking interdecadal changes in British river ecosystems to water quality and climate dynamics. *Global Change Biology*, *20*(9), 2725–2740. https://doi.org/10.1111/gcb.12616

Verheyen, J., Delnat, V., & Theys, C. (2022). Daily temperature fluctuations can magnify the toxicity of pesticides. *Current Opinion in Insect Science*, *100*, 919.

Vernier, F., Leccia-Phelpin, O., Lescot, J. M., Minette, S., Miralles, A., Barberis, D., Scordia, C., Kuentz-Simonet, V., & Tonneau, J. P. (2017). Integrated modeling of agricultural scenarios (IMAS) to support pesticide action plans: The case of the Coulonge drinking water catchment area (SW France). *Environmental Science and Pollution Research*, *24*(8), 6923–6950. https://doi.org/10.1007/s11356-016-7657-2

Verschoor, A. J., Vink, J. P. M., de Snoo, G. R., & Vijver, M. G. (2011). Spatial and temporal variation of watertype-specific no-effect concentrations and risks of Cu, Ni, and Zn. *Environmental Science & Technology*, *45*(14), 6049–6056. https://doi.org/10.1021/es2007963

Wagner, C., & Løkke, H. (1991). Estimation of ecotoxicological protection levels from NOEC toxicity data. *Water Research*, *25*(10), 1237–1242. https://doi.org/10.1016/0043-1354(91)90062-U

Whelan, M. J., Linstead, C., Worrall, F., Ormerod, S. J., Durance, I., Johnson, A. C., Johnson, D., Owen, M., Wiik, E., & Howden, N. J. K. (2022). Is water quality in British rivers "better than at any time since the end of the industrial revolution"? *Science of the Total Environment*, *157*, 014. https://doi.org/10.1016/j.scitotenv.2022.157014

Woodward, G., Perkins, D. M., & Brown, L. E. (2010). Climate change and freshwater ecosystems: Impacts across multiple levels of organization. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, *365*(1549), 2093–2106. https://doi.org/10.1098/rstb.2010.0055

Wright, J. F., Armitage, P. D., Furse, M. T., & Moss, D. (1989). Prediction of invertebrate communities using stream measurements. *Regulated Rivers: Research & Management*, *4*(2), 147–155.

WWF. (2016). *Living planet: Report 2016: Risk and resilience in a new era*. World Wide Fund for Nature.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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