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Characterization factors for the impact of climate change on freshwater fish species

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ABSTRACT

Human activities increasingly threaten the highly biodiverse freshwater ecosystems. Life Cycle Assessment (LCA) is a useful tool to quantify the impacts of products and services on freshwater biodiversity. Current methodologies in LCA address the impact of climate change on freshwater fish diversity by changes in average river discharge only. Given the ectothermic nature of fish, previous studies have highlighted the importance of including water temperature changes as a driver of species loss. Moreover, the impact of climate extremes might be more important than changes in average conditions. In this study, we derived new characterization factors for 207 individual greenhouse gas (GHG) emissions that quantify the impact of an emission change on freshwater fish, accounting for climate-driven changes in both streamflow and water temperature extremes. We combined a novel dataset of fish range climate threats with a newly developed species-area relationship to quantify global freshwater fish extinction risks at various global warming levels. The global characterization factors range from 0.00 to $4.56 \cdot 10^{-10}$ Potentially Disappeared Fraction (PDF)·yr·kg^{-1}. Our results imply that freshwater fish diversity impacts per kg of GHG emission have been underestimated in previous LCA methods that excluded the impact of water temperature and climate extremes, as the newly developed effect factor is higher by 172%. Future contributions should focus on increasing taxonomic coverage (e.g., by including lentic fish species and macro-invertebrates) and developing complementary models to reflect other aspects of biodiversity in LCA.

1. Introduction

Freshwater ecosystems are characterized by a high diversity of species and habitats. While they span only 2.3% of the global surface, they accommodate 9.5% of the total animal species (Reid et al., 2019). However, freshwater biodiversity is more threatened than terrestrial and marine biodiversity (Collen et al., 2014; Wiens and Barnosky, 2016). Freshwater species populations declined by 84% between 1970 and 2016, a remarkably higher percentage than the average of 68% for all species (World Wildlife Fund, 2020). Multiple human-induced drivers are responsible for this plunge: over-exploitation, pollution, flow regulation, land-use change, invasive species, and climate change (Dudgeon, 2019; Reid et al., 2019). Climate change is considered a rising threat to freshwater species and can exacerbate these already existing threats (World Wildlife Fund, 2018; Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, 2019).

A freshwater biodiversity crisis can have large consequences on water and food availability for humans, human health, resilience to natural hazards, and even climate change (Cowx and Portocarrero Aya, 2011). The ecosystem services provided by freshwater ecosystems exceed a value of 4 trillion US dollar annually (Flitcroft et al., 2019). There is a high urgency for society to maintain healthy freshwater ecosystems as they are essential to human well-being and sustain livelihoods. Integrating freshwater biodiversity into decision-making processes is paramount to solving the freshwater biodiversity crisis (Darwall et al., 2018).

Life Cycle Assessment (LCA) is an important decision-making tool to guide the transition toward more sustainable products and services (Guinée et al., 2002). It offers a standardized approach to quantify environmental sustainability and to identify hotspots (large impacts)

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across the life-cycle of products, processes, or supply chains (Hellweg and Milà i Canals, 2014). LCA is an inclusive tool, as it can address multiple impact categories (e.g., climate change, eutrophication, and land use; Ciacci and Passarini, 2020). However, the inclusion of biodiversity in LCA is incomplete, as several pressures on biodiversity are not fully covered in LCA, especially related to the freshwater realm (Curran et al., 2016; Winter et al., 2017). Within the LC-IMPACT and ReCiPe impact families, freshwater ecosystems damage pathways are identified for global warming, water consumption, ecotoxicity, and eutrophication (Huijbregts et al., 2016; Verones et al., 2020). In both impact families, the global warming impact category is modeled by Hanafiah et al. (2011). Hanafiah et al. (2011) developed a methodology that builds upon the species-discharge relationship, which predicts species richness from the average discharge at the mouth of a river basin. Based on this relationship, they estimate the Potentially Disappeared Fraction (PDF) of freshwater fish species per change in average discharge, which, in turn, is driven by a change in global mean temperature. Changes in water temperature due to climate change are not included in this method. Yet, fish are ectothermic organisms (i.e., they cannot self-regulate their body temperature) and therefore their habitat is constrained by water temperature and its related changes (Comte and Olden, 2017; Knouft and Ficklin, 2017). Furthermore, the geographic coverage in Hanafiah et al. (2011) is limited, as river basins above 42°N were excluded due to limitations in the applicability domain of the species-discharge relationship.

A recent study by Barbarossa et al. (2021) showed that freshwater fish species at the global scale are more severely threatened by water temperature alterations than streamflow alterations. An impact pathway solely considering reduced river discharge may thus underestimate extinction risk. Further, extreme events have been shown to be better predictors for estimating extinction risk than long-term averages (Liu et al., 2015; Román-Palacios and Wiens, 2020). Therefore, the inclusion of climate extremes' impacts might lead to improved accuracy in the estimation of extinction probabilities and unveil hidden impacts. In addition, novel datasets on the spatial distribution of freshwater species have recently become available to increase geographical and taxonomic coverage (Barbarossa et al., 2021).

Here, we develop novel characterization factors for the impact of climate change extremes on freshwater fish biodiversity. We used a new dataset by Barbarossa et al. (2021) on fish range threats due to climate-driven changes in streamflow and water temperature extremes for 11,425 riverine fish species, or 76% of the total freshwater fish species. We translated the range threats to extinction risk by developing a species-area relationship for riverine fish species. We converted global extinction risk to characterization factors for 207 greenhouse gases (GHGs). The characterization factors can be used in the impact assessment phase of LCA studies to convert inventory data on GHG emissions into an estimate of the impact on freshwater fish biodiversity. Finally, we apply the newly developed characterization factors in a case study on the transportation fuels petrol and diesel and their equivalents biopetrol and biodiesel to demonstrate their use. We compare the freshwater biodiversity impacts through means of the newly derived characterization factors as well as the LC-impact categories on climate change, water stress, and eutrophication.

2. Methodology

The characterization factors developed in this study report freshwater species extinction risk, expressed as PDF of species, due to global warming. Woods et al. (2018) recommend the unit of PDF to stimulate consistency among LCA studies. Extinction risk is defined as the proportion of species that are committed to extinction (Thomas et al., 2004). Characterization factors consist of fate factors and effect factors and are calculated as follows:

$$CF_{x,w} = FF_{x,w} \bullet EF_w = \frac{dT_x}{dGHG_x} \bullet \frac{dE_w}{dT_w} \tag{1}$$

Where CF is the global characterization factor [PDF·yr·kg^{-1}] for the type of GHG × and the warming level w, FF is the global fate factor [°C·yr·kg^{-1}], and EF is the global effect factor [PDF·°C^{-1}]. Fate factors translate the impact of GHGs emitted to the atmosphere dGHG [kg·yr^{-1}] to an increase in global air temperature dT [°C]. Effect factors translate the increase in global air temperature dT [°C] to global extinction risk dE [PDF]. The characterization and the effect factors are defined for the global scale since the fate factors are global by definition. This is due to the short tropospheric mixing time of one year, ensuring that GHGs spread globally during their lifetime (De Schryver et al., 2010; Hauschild and Huijbregts, 2015). The steps required to calculate the characterization factors are summarized in Fig. 1.

2.1. Fate factor

We employed fate factors according to ReCiPe (Huijbregts et al., 2016) for 207 GHGs. The fate factors are calculated as follows:

$$FF_{x,w} = GWP_{x,w} \bullet IAGTP_{CO_2,w} \tag{2}$$

Where FF is the global fate factor, GWP is the global warming potential (dimensionless) [-], and IAGTP is the integrated absolute global mean temperature change potential relative to CO_2 [°C·yr·kg^{-1}]. GWPs are provided by Huijbregts et al. (2016) and the IAGTP by Joos et al. (2013). A critical value choice is the time horizon. Extended characterization factors in LC-IMPACT are based on a time horizon of 100–1000 years to reflect long-term impacts.

2.2. Effect factor

2.2.1. From threatened ranges to extinction risk

The global extinction risk needed for the numerator of the effect factor in Eq. (1) is calculated based on data on the species-specific percentage of range threatened by climate extremes (Barbarossa et al., 2021). The dataset comprises the percentage of range threatened at different warming levels for 11,425 riverine fish species. The portion of range threatened is calculated from the sum of the area of the five arc-minute grid cells in which at least one or more thresholds for water temperature or streamflow extremes are exceeded. Thresholds are set for minimum and maximum weekly flow, the number of zero flow weeks, and the minimum and maximum weekly water temperature. Scenarios are created by combining five global climate models and four representative concentration pathways, aggregated to the warming levels 1.5, 2.0, 3.2 and, 4.5 °C. There are two dispersal scenarios: the no-dispersal scenario and the maximal-dispersal scenario.

We converted the threatened ranges into global extinction risk at each warming level using an extinction metric (Thomas et al., 2004). There are three extinction metrics. The first metric (Eq. (3)) incorporates the classic species-area relationship and analyses the overall changes in area distributions across all species. This metric is biased towards species with large distributional areas. The second metric (Eq. (4)) addresses the bias of the first metric by calculating the change in distribution area averaged across species. The third metric (Eq. (5)) takes this a step further by calculating the extinction risk of each species before averaging across species. This metric assumes that the extinction risk of each species weighs equally, which is particularly relevant for endemic species that are prone to extinction and tend to have small geographic ranges (Lewis, 2006; Parmesan, 2006). Given the more even weighting, we adopted the third metric in the calculation of our effect factors (Eq. (5), and in this comparison, we refer to it as the benchmark metric. Also, we compare the extinction risk of single species using the species-specific part of the benchmark extinction metric and an average of the warming level and dispersal scenarios.

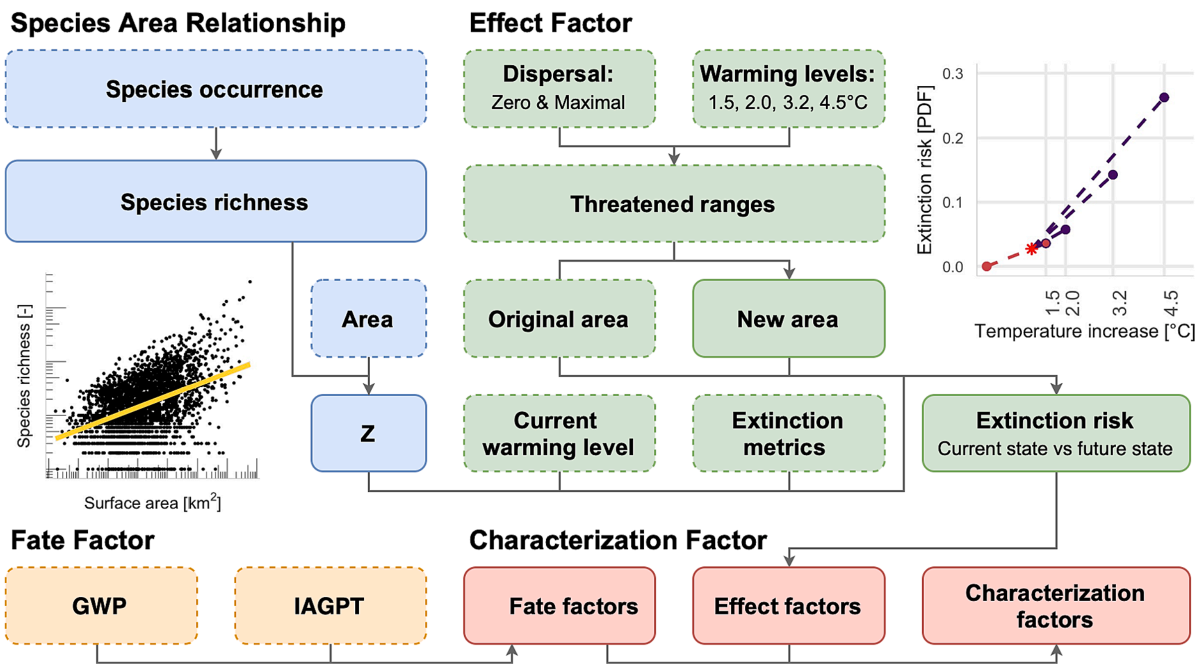

Fig. 1. Methodological framework for the calculation of the characterization factors. The dotted lines show background data, for which the sources are provided in the text below.

$$E_w = 1 - \left(\frac{\sum A_{new,w}}{\sum A_{original,w}}\right)^z \tag{3}$$

$$E_w = 1 - \left\{\frac{1}{n}\left[\frac{A_{new,w}}{A_{original,w}}\right]\right\}^z \tag{4}$$

$$E_w = \frac{1}{n}\sum\left[1 - \left(\frac{A_{new,w}}{A_{original,w}}\right)^z\right] \tag{5}$$

The extinction risk E for each warming level w is expressed in PDF. The n refers to the number of species [number of species], and z is a coefficient [-] derived from the species-area relationship (SAR). $A_{original,w}$ refers to the initial area available and $A_{new,w}$ refers to the area which remains available under the threat of global warming, both expressed in km^2. $A_{original,w}$ and $A_{new,w}$ were derived from Barbarossa et al. (2021). To derive the z coefficient for freshwater fish for Eqs. (3)–(5), we developed a SAR using the power relationship in Eq. (6) as the SAR currently only exists for terrestrial species. The classic SAR is linearized by double-logarithmic transformation to derive the slope, i.e., the z coefficient. We extracted riverine fish species richness and drainage area for 14,953 diadromous and non-diadromous species and 3,119 river basins from Tedesco et al. (2017), which cover more than 80% of the earth's surface. We summed the different species per river basin based on occurrence data at the river basin level. Only native freshwater species were considered since exotic species can influence the slope of the relationship (Baiser and Li, 2018).

$$S = cA^z \tag{6}$$

where S is species richness [number of species], A is the area [km^2], and c and z are constants [-].

2.2.2. From extinction risk to effect factor

Four effect factors are calculated for the warming levels 1.5, 2.0, 3.2 and 4.5 °C and for both dispersal scenarios. The calculation follows the average approach, where the current state and the prospective future state of the extinction risk and temperature are required to calculate the effect factors (Hanafiah et al., 2011).

To calculate the current global warming level, we used data from the World Meteorological Organization (2022), which annually reports the global mean temperature increase compared to the pre-industrial baseline (1850–1900), averaged from six datasets. We considered a long-term average of 10 years, specifically the years 2013 to 2022, to account for inter-annual fluctuations, remain close to the current situation, and reflect the recent stark increase in global mean temperatures (World Meteorological Organization, 2022). This results in a global mean temperature increase of 1.14 °C.

To calculate the extinction risk at the current state, the relationship between the extinction risk and global mean air temperature is determined (Fig. 2). We assumed linearity between the origin and the first considered warming level at 1.5 °C, given the few data points available to derive the relationship.

As for the prospective future state, we consider the four different warming levels and calculate average effect factors according to Eq. (7).

$$EF_w = \frac{E(w) - E(1.14)}{w - 1.14} \tag{7}$$

where EF is the effect factor [PDF·°C^{-1}] for each warming level w [°C] and E is the global extinction risk [PDF].

Finally, an average is calculated from the effect factors for the four different warming levels and two dispersal scenarios.

2.3. Grid-cell level contribution to global extinction risk

To reveal hotspots of species loss, we determined the contribution of each grid cell to the global species extinction risk. For each species, the global extinction risk is partitioned across the grid cells where it occurs, proportionally to the area of the grid cell. For each grid cell, the partitioned extinction risks are summed and divided by the total extinction risk to obtain the local contribution. The partitioned extinction risk (Ep) per species s and grid cell i is calculated according to Eq. (8). Eq. (8) is based on the extinction metrics from Eq. (5), which requires the global original and newly estimated areas (A) available for a species.

$$Ep_{s,i} = \left(1 - \left(\frac{A_{new,s,global}}{A_{original,s,global}}\right)^z\right) \bullet A_i \tag{8}$$

Finally, the percentage contribution per grid cell is determined by

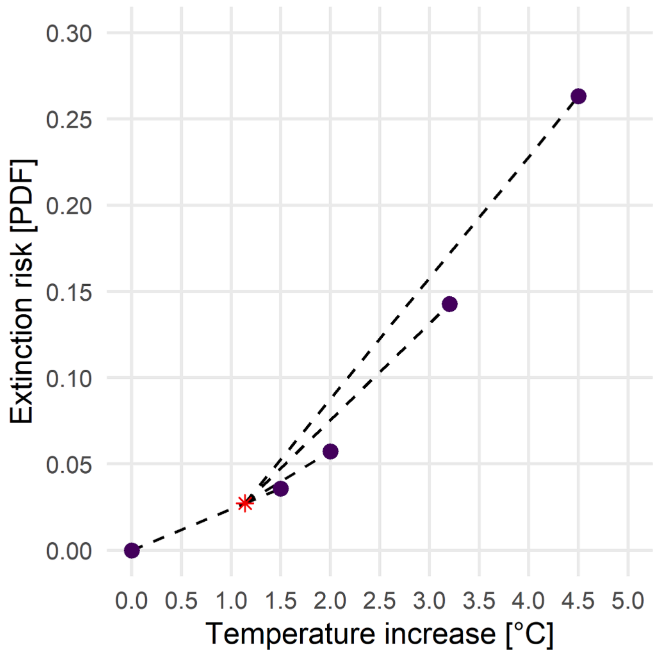

Fig. 2. Extinction risk [PDF] against increased global air temperature [°C]. The current situation at 1.14 °C is plotted as a red asterisk and is derived using the slope between 0 and 1.5 °C. The four average effect factors are the distance between the current situation and the chosen warming level. The extinction risk values in this graph represent the zero-dispersal scenario. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

summing up the partitioned extinction risks for all species occurring in the grid cell and dividing by the cumulative sum of partitioned extinction risks (Eq. (9)).

$$Ep_i = \frac{\sum_{s=1}^{n} Ep_{s,i}}{\sum_{i=1}^{n}\sum_{s=1}^{n} Ep_{s,i}} \bullet 100\% \tag{9}$$

2.4. Analysis of variance

We performed a two-way analysis of variance (ANOVA) to identify which factors influence the effect factors. The first factor for the ANOVA is the choice for the extinction metrics. Three levels are compared: the benchmark metric in Eq. (5) and two alternative equations, Eq. (3) and (4), by Thomas et al. (2004). The second factor in the ANOVA analysis is the warming level, which has four values: 1.5, 2.0, 3.2, and 4.5 °C. The third factor is the dispersal scenario, with two levels: the no-dispersal scenario and the maximal-dispersal scenario. The effect factors are calculated for all the factors with equal levels to create a balanced design. Assumptions of equal variance have been assessed in Fig. S1.

2.5. Biofuels case study

We applied the newly developed characterization factors to a case study on transportation fuels. The conventional fuels diesel and petrol are compared against biodiesel and biopetrol for the functional unit of 1 km of transport by a passenger car. The modelling is performed in CMLCA using data from Ecoinvent version 3.4 (Wernet et al., 2016). Inventory data is depicted in Tables S1 and S2. The fuel ratios in Table S1 are derived by scaling data from Pfister and Scherer (2015), who based their analysis on Ecoinvent version 2.2 data (Frischknecht et al., 2005). The other inventory processes listed in Table S2 are based on Ecoinvent version 3.4 data.

Impact scores are obtained by multiplying the inventory data with characterization factors. The new characterization factors for the impact of climate change on freshwater ecosystems are compared with the LC-IMPACT freshwater ecosystem quality categories climate change, eutrophication, and water stress. Since the extended LC-IMPACT climate change category adopts a time horizon of 1,000 years and averages across multiple climate scenarios, the newly developed climate change characterization factors are calculated for the same time horizon and averaged for the warming levels to allow comparability.

3. Results

3.1. Effect factors

The effect factors resulted in a range of $4.47 \cdot 10^{-3}$ – $7.02 \cdot 10^{-2}$ PDF·°C^{-1} according to the warming levels assessed in this study (Fig. 3 and Table S3). We used a z exponent (see Eqs. (3)–(6)) of 0.21, as resulting from the slope of the log-linear regression for the species-area relationship (Fig. S2; p-value < 0.001).

All species except for *Ichthyscopus fasciatus* show increased extinction risk. Three species, *Amphilius opisthophthalmus*, *Thoracochromis moeruensis*, and *Sundadanio atomus*, are expected to have zero new area available under the various scenarios and are thus expected to go extinct. The mean and median values for single species extinction risk are $8.49 \cdot 10^{-2}$ and $5.81 \cdot 10^{-2}$ (dimensionless unit) respectively. A full list of species-specific extinction risks can be found in Supporting Information II.

3.2. Spatial variation

Spatially, the grid-cell level contribution to the global extinction risk was highly variable, reflected by a range spanning $7.36 \cdot 10^{-10}$ – $6.62 \cdot 10^{-2}$ % across all warming levels. The pattern is similar for the different warming levels, with differences between grid cells increasing at higher warming levels (Figs. 4, S3, S4, and S5). The highest contributing grid cells are found in Mediterranean and tropical areas, while grid cells at higher altitudes show lower extinction risk contribution values. South America has the largest summed contribution on a continental scale.

3.3. Analysis of variance

The factor influencing the effect factors the most was the dispersal scenario, closely followed by the warming levels (Table 1). This shows that especially the modelling choices in the dispersal scenario and warming levels explain around 85% of the variation in the effect factors.

3.4. Characterization factors

The global characterization factors for the 207 GHGs considered in our study range 0 – $3.50 \cdot 10^{--11}$ PDF·yr·kg^{-1} for the 100-year time horizon and 0 – $4.56 \cdot 10^{-10}$ PDF·yr·kg^{-1} for the 1000-year time horizon (Supporting Information III). These are based on effect factors calculated with the benchmark extinction metric and an average of all warming levels and dispersal scenarios. The characterization factors are higher for the 1000-year time horizon and vary amongst the GHGs (Fig. 5). The largest characterization factors found are for the GHG sulfur hexafluoride, and the lowest characterization factors are zero for various GHGs (due to the fate factors).

3.5. Biofuels case study

In this case study, the newly developed characterization factors are applied to compare petrol, biopetrol, diesel, and biodiesel impact scores across various impact categories addressing freshwater ecosystem quality (Supporting Information IV). According to Fig. 6, there are large differences in the magnitude of the impact scores across the various impact categories. Water stress has a high order of magnitude of up to

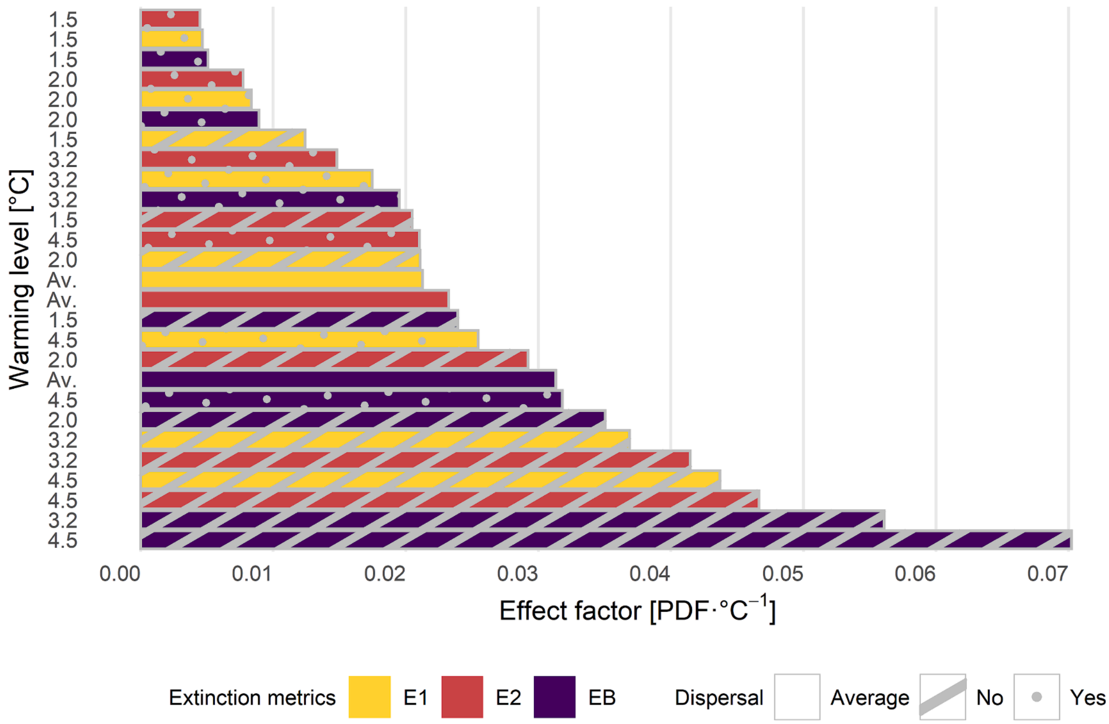

Fig. 3. Effect factors in in PDF·°C^{-1} for the different extinction metrics by Thomas et al. (2004), dispersal scenarios and warming levels. Averages (av.) refer to the effect factor based on the average of the warming levels and both dispersal scenarios.

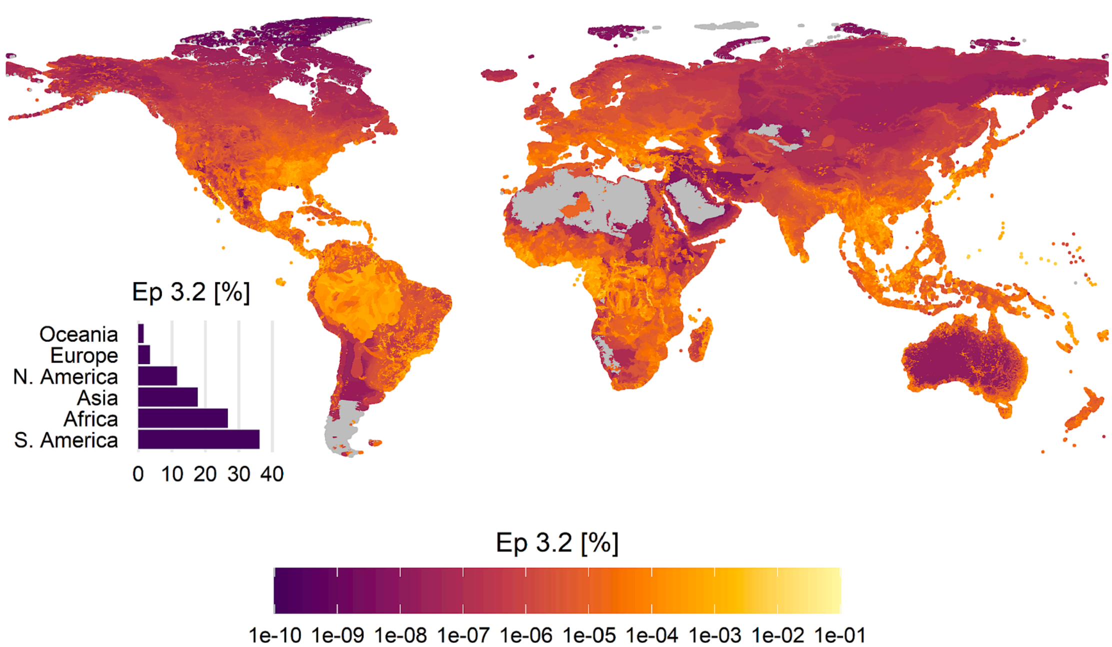

Fig. 4. Grid-cell level contribution in percentage points (Ep) to global extinction risk at a warming level of 3.2 °C. Maps for the grid-cell level contribution of the warming levels 1.5, 2.0 and 4.5 °C can be found in Figs. S3 – S5. Gray shows missing values, either because there are no species occurring or there is no data available for this area. The inset shows the contribution per continent, obtained by summing the Ep values across the grid-cells of a continent.

10^{-14}, while eutrophication has a magnitude of 10^{-19}. The impact scores of the new climate change category increased approximately 173% compared to the LC-IMPACT climate change category. The conventional fuels are the better alternatives when considering eutrophication and water stress. For climate change, the impact score of biodiesel is the lowest, but biopetrol performs slightly worse than petrol.

4. Discussion

4.1. Comparison with other studies

4.1.1. Freshwater effect factor

Hanafiah et al. (2011) derived global effect factors via the species-discharge relationship, while the effect factors proposed in this study are derived via assessing species-specific threatened ranges due to

Table 1
ANOVA for the various influencing factors, where the variance in percentage points is calculated based on the sum of squares. All factors were statistically significant at a significance level of 0.05.

Factor	Extinction metrics	Warming level	Dispersal	Residuals
Explained variance (%)	6.6	41.2	43.5	8.6

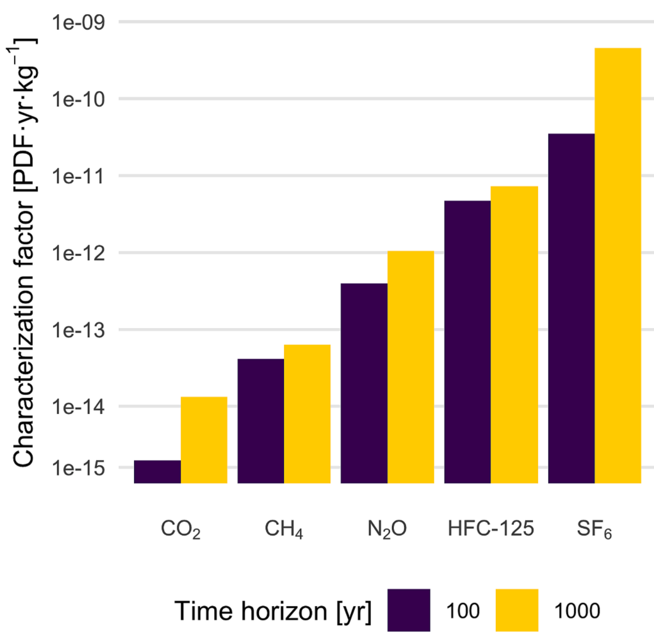

Fig. 5. Characterization factors in PDF·yr·kg^{-1} for a selection of the greenhouse gases and the various cultural perspectives. The characterization factors are based on the effect factor for the benchmark extinction metric and an average of the warming levels and dispersal scenarios.

exceeding extremes in water temperature and flow habitat factors. LC-IMPACT (Steinmann and Huijbregts, 2019) adapted the effect factor calculated by Hanafiah et al. (2011) to consider non-marginal changes and arrived at an effect factor of 1.15·10^{-2} PDF·°C^{-1}. The newly developed effect factor for the benchmark equation metrics in our study is 172% higher. Only a few effect factors based on the maximal-dispersal scenario and one effect factor based on a global warming level of 1.5 °C and the no-dispersal scenario were lower.

4.1.2. Terrestrial effect factor

The global average effect factor of 3.7·10^{-2} PDF·°C^{-1} for terrestrial species in the impact families ReCiPe (Huijbregts et al., 2016) and LC-IMPACT (Steinmann and Huijbregts, 2019) is lower than a selection of the new effect factors based on the no-dispersal scenario (namely for the warming levels 3.2 and 4.5 °C and all extinction metrics, and for the average warming level and the benchmark extinction metric). The general expectation that freshwater species are more severely threatened by climate change than terrestrial species (Collen et al., 2014) may still hold if more anthropogenic pressures are included in the model. It is important to consider the methodological differences between the studies considering the assessed warming levels, as the ANOVA showed this is a highly influential parameter. While all studies used averages of multiple warming level scenarios, the terrestrial effect factor is based on extinction predictions for only two warming levels: 0.8 °C and 4.3 °C compared to pre-industrial levels (Urban, 2015).

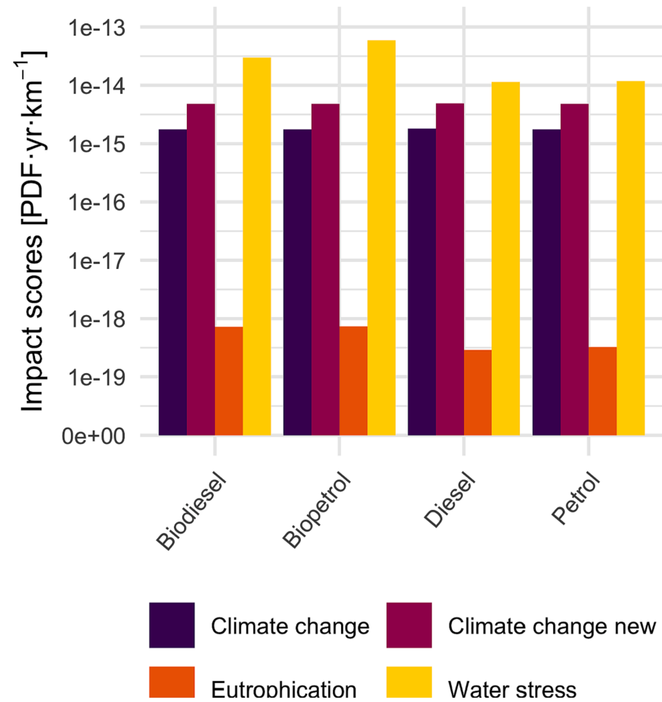

Fig. 6. Impact scores in PDF·yr·km^{-1} for the LC-IMPACT freshwater ecosystem quality categories climate change, eutrophication, and water stress and the newly developed characterization factors (1000-year time horizon, mean value across the warming levels) for different types of fuel. The scale is logarithmic.

4.1.3. Characterization factors

The global characterization factors across the various GHGs for the freshwater realm in LC-IMPACT range from 0.00 to 1.67·10^{-10} PDF·yr·kg^{-1} for the 1000-year time horizon. These are 2.7 times lower than the ones calculated in this study for the same time horizon (0.00 – 4.56·10^{-10} PDF·yr·kg^{-1}). The inclusion of direct water temperature effects, not included in Hanafiah et al. (2011), can explain the higher values. Verones et al. (2010) found that seasonal temperature fluctuations resulted in differences up to five orders of magnitude for the effect of thermal pollution on freshwater fish in the Rhine. Another difference between the study is the selection of river basins: this study calculated average effect factors for 9,176 river basins, while Hanafiah et al. (2011) limited the selection to 326 river basins. Fig. 4 has shown that certain areas have a larger contribution to the global extinction risk, e.g., the tropics. This means potential biodiversity hotspots might not have been included by Hanafiah et al. (2011). On the other hand, Hanafia et al. excluded river basins located below 42 °N, which have shown a relatively small contribution to the global extinction risk according to our results (Fig. 4).

4.1.4. Spatial and inter-species variability

The spatial patterns of effect factors are similar to observed patterns for the potentially affected fraction of species reported by Barbarossa et al. (2021). They found that the spatial patterns reflect mostly an increase in maximum water temperature. As for variations in fish species responses, these were found to be mostly related to habitat type, current range size, IUCN threat status and body length (Barbarossa et al., 2021).

4.2. Limitations

This study is based on the results of Barbarossa et al. (2021) which comprehensively assessed threats to geographic ranges of riverine fish species by examining hydrological extremes' species-specific thresholds for five habitat parameters concerning water temperature and streamflow. Therefore, the modeling limitations of Barbarossa et al. (2021) also apply to this study. For example, seasonal effects are not considered in the set of variables used in their study but could be important, especially if species are adapted to specific water flow and temperature patterns (Barbarossa et al., 2021).

While we acknowledge that our study is limited only to riverine species due to modeling limitations in water temperature stratification of lakes, riverine species are considered a representative proxy for freshwater biodiversity (Izzo et al., 2016). Nevertheless, limiting biodiversity assessment to one taxon remains an important limitation in LCA, as highly sensitive species can be overlooked (Curran et al., 2011). For instance, Tendall et al. (2014) showed that macro-invertebrates might be more representative of the ecosystem quality status in smaller streams and more vulnerable to changes in discharge than fish species. Sensitive macro-invertebrate taxa such as Ephemeroptera, Plecoptera, and Trichoptera (EPT) decrease in richness in waters with increased temperatures (Karaouzas et al., 2019), while other macro-invertebrate taxa may experience increases in richness (Chessman, 2009).

According to the ANOVA, dispersal was the most influencing factor. Barbarossa et al. (2021) provided a zero- and a maximal-dispersal scenario. Since these are both extreme scenarios, an average was calculated from both scenarios. Dispersal of riverine fish species is restricted due to the dendritic structure of river basins, natural barriers, and fragmentation, yet the extent to which dispersal occurs remains poorly understood (Harte and Kitzes, 2012; Barbarossa et al., 2020). Fragmentation is expected to increase due to drying impacts arising from climate change (Jaeger et al., 2014; Knouft and Ficklin, 2017). This might impair the ability of fish to combat climate change by dispersal. Range expansion can also occur due to potential positive effects of climate change, e.g., in cold waters.

Yousefi et al. (2020) show that climate change has winners and losers; some species lose while others gain habitat. A trade-off here is that the winners of climate change could be invasive species, which can displace native species and alter trophic webs (Flitcroft et al., 2019). Hanafiah et al. (2013) developed characterization factors for the introduction of exotic species for the transportation of goods through the Rhine-Main-Danube waterway. They assessed the relative contribution of the introduction of exotic species, global warming, and other impact categories by applying characterization factors (including the characterization factors for global warming developed by Hanafiah et al. (2011)) to a case study of transported goods. The introduction of exotic fish species was found to explain 70–85% of the impact on freshwater biodiversity. Thus, range expansions might not necessarily yield positive effects on biodiversity.

Extinction risk is a common way to estimate PDF in LCA (Curran et al., 2016). However, it introduces uncertainties related to the negligence of ecological principles. Dynamics at the ecosystem level do not typically fit the stochastic processes leading to extinction (Curran et al., 2011; Tedesco et al., 2013). The vulnerability of species to stochastic events is highly variable, due to different habitat preferences, small population sizes, or limited ranges (Moyle et al., 2013). Examples of stochastic events triggered due to global warming are large floods (Mirza, 2011). The extinction risk may be underestimated since stochastic events are not included (Bellard et al., 2012). The negligence of species adaptation, on the other hand, is classified as a highly overestimated factor in the calculation of extinction risk (Bellard et al., 2012). Species adaptation frequently occurs at the edge of species' ranges and may be important for particular species (Knouft and Ficklin, 2017), especially for those with short generation time (Radinger et al., 2017). However, the speed of climate change is expected to exceed the adaptation or dispersal ability of freshwater species (Radinger and Wolter, 2015; Radinger et al., 2017; Reid et al., 2019).

The extinction metrics are built upon the SAR. An assumption by the SAR is that species are equally distributed across space. This explains why the SAR is sensitive to the size of the area for data collection (Pereira, Borda-De-Água and Martins, 2012). The z coefficient is calculated based on the SAR drawn from the Tedesco et al. (2017) compilation of basins and species occurrences. However, this database retains many river basins with low species richness (e.g., below five species), which might be unrealistic. One reason for the low species richness is that all occurrences that were not identified at the species level were excluded (Tedesco et al., 2017).

4.3. Outlook

Future studies should focus on expanding taxonomic coverage to include lentic species and other taxonomic groups to improve the representativeness of species coverage for freshwater biodiversity. This study focuses on the species richness metric, which describes the community level and neglects the genetic and landscape levels of biodiversity. Complementary models can be useful to compare other facets of biodiversity to describe ecosystem health more accurately (Curran et al., 2011; Tendall et al., 2014). A valuable, complementary metric for LCA studies is functional diversity, which considers the functional traits of species and reflects ecosystem functioning better than species richness (Scherer et al., 2020). To further our understanding of the different impacts on freshwater biodiversity across the different life cycle stages of a product, future studies should focus on harmonizing impact categories within existing life cycle impact assessment families such as LC-IMPACT (Verones et al., 2020). For example, the characterization factors for the impact of the introduction of exotic species (Hanafiah et al., 2013) on freshwater biodiversity can only be applied to the case of transported goods. Methods use differing units, and therefore conclusions on the contribution of the different stressors cannot be established. Finally, numerous stressors are lacking in current LCIA methodologies, and more research is needed to address the complex interplay of threats to freshwater biodiversity (Dudgeon, 2019).

5. Conclusion

We developed a method to translate the impact of climate change on freshwater fish diversity into characterizations factors for LCA applications. Global extinction risks are quantified based on 11,425 riverine fish species-specific threatened ranges estimated by Barbarossa et al. (2021). The z coefficient needed for the extinction metrics is determined by developing, in this study, a species-area relationship specific to riverine fish species. Average effect factors are derived from mapping global extinction risk against corresponding global mean temperature increases. Finally, characterization factors are derived by multiplying the effect factors with fate factors based on Huijbregts et al. (2016).

LCA practitioners can use the characterization factors to translate inventory data on GHG emissions arising throughout the life cycle of a product into an estimate of the fraction of freshwater species extinction. The new set of characterization factors is 2.7 times higher than previously calculated ones, stressing the importance of considering extreme values and including water temperature variables besides streamflow variables when assessing the impacts of climate change in LCA. The new advances can contribute to a more comprehensive understanding of the environmental impact of products and services on freshwater fish biodiversity.

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CRediT authorship contribution statement

Sif de Visser: Methodology, Formal analysis, Visualization, Writing – original draft. **Laura Scherer:** Methodology, Supervision, Writing – review & editing. **Mark Huijbregts:** Methodology, Writing – review & editing. **Valerio Barbarossa:** Conceptualization, Methodology, Writing

– review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110238.

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