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Original Articles

Global characterization factors for quantifying the impacts of increasing water temperature on freshwater fish

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ABSTRACT

Water temperature is an abiotic master variable for the survival of aquatic organisms. Global warming alters the thermal regimes of rivers and, thus, poses a threat to freshwater biodiversity. To address the impacts of water temperature changes related to global warming on freshwater fish species in life cycle assessment (LCA), we developed spatially explicit characterization factors (CFs) for 207 greenhouse gases under four representative concentration pathways. We calculated fate factors by using the output of a global hydrological model fully coupled with a dynamic water temperature model. We developed six species sensitivity distribution curves for two thermal effects (i.e., lethal and sub-lethal) to derive effect factors, which take the differences in sensitivity between climate regions into account. The regional CFs for CO_2 ranged from 2.91×10^{-22} to 6.53×10^{-18} PAF·yr/kg for sub-lethal effects and from 1.98×10^{-22} to 4.58×10^{-18} PDF·yr/kg for lethal effects, depending on the river watersheds and future climate scenarios. To identify the contribution of regional impacts on freshwater fish to their potential global extinction, the regional CFs were converted into global CFs. The largest CFs always occur in the tropical watersheds. The regional impacts in the Amazon watershed contribute the most to the global freshwater fish species extinction. This study contributes to assessing the potential impacts on freshwater biodiversity from global warming from a new cause-effect pathway in LCA.

1. Introduction

Freshwater ecosystems support disproportionate levels of global biodiversity within less than 1 % of the Earth's surface (Dudgeon, 2014). Freshwater biodiversity is experiencing a dramatic decline in both abundance and richness of species (Dudgeon et al., 2006; Groombridge and Jenkins, 2000), and extinction rates may be about to accelerate in the coming years (Johnson et al., 2017). In addition, freshwater ecosystems are the most threatened ecosystems, facing a higher risk of degradation than their terrestrial or marine counterparts (Dudgeon et al., 2006; Sala et al., 2000).

Climate change has emerged as an increasingly important driver of freshwater transformation (Woodward et al., 2010). The abiotic conditions for freshwater species are affected through changes in water availability and water temperature caused by changing air temperature and precipitation and through interaction with other stressors (e.g., eutrophication) (Ficke et al., 2007).

While streamflow is considered the master variable to describe the habitat of freshwater fish and will be heavily affected by climate change (Kernan et al., 2010; Poff, 2018), recent evidence showed that climate-change driven changes in water temperature could affect the habitat of fish species to a much larger extent (Barbarossa et al., 2021). Indeed, water temperature is the ultimate indicator for a warming effect. Moreover, water temperature is a limiting factor for determining the physiology and behavior of aquatic species (Özdemir and Altindağ, 2007; Woodward et al., 2010). Freshwater fish regulate their body temperature depending on the surrounding water temperatures. Temperatures outside of their optimal thermal range can lead to sub-lethal biological reactions and in extreme cases to lethal effects (Johnson and Kelsch, 1998; Vannote and Sweeney, 1980). Sub-lethal effects, such as loss of equilibrium, can hamper freshwater fish movements to cooler locations (Dallas, 2018; Dallas and Ross-Gillespie, 2015). Lethal effects

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directly lead to death and contribute to changes in species distribution and species richness (Currie, 1991).

The thermal tolerance of many freshwater fish species has been recorded in laboratory experiments (Lapointe et al., 2018; Lattuca et al., 2018; Underwood et al., 2012; Xia et al., 2017) and interest in comprehensively assessing the freshwater fish responses to changes in water temperature related to climate change is increasing in light of an increased interest for sustainability assessments in general (Barbarossa et al., 2021; Huang et al., 2021; Olusanya et al., 2018; Rosenzweig et al., 2007).

Life cycle assessment (LCA) is such a methodology for assessing the sustainability of a product or service by assessing its potential environmental impacts through its entire life cycle (Finkbeiner et al., 2006). Current Life cycle impact assessment (LCIA) models dealing with climate change impacts related to ecosystem quality distinguish between different realms (terrestrial and freshwater) (De Schryver et al., 2009; Hanafiah et al., 2011; Verones et al., 2020). However, the models related to climate change impacts in freshwater ecosystems are currently restricted to the effect of changing river water flows due to changed precipitations patterns, and are limited in coverage (Hanafiah et al., 2011). Hence, currently no LCIA model quantifying the adverse effects of climate change on freshwater ecosystems related to changes in the thermal regime of a river exists.

To close this research gap, we develop spatially-differentiated characterization factors (CFs) for the impact of increasing water temperatures on freshwater fish species due to climate change. Our endpoint CFs for lethal effects translating the loss of species richness in potentially disappeared fractions of species (PDF) (Curran et al., 2011; Woods et al., 2018), as recommended by the Life Cycle Initiative (Verones et al., 2017). Since, thermal stressors can also cause sub-lethal effects, we also calculated CFs quantifying the potentially affected fraction of species (PAF) from non-lethal impacts.

The CFs are presented at pixel and watershed level and to identify the contribution to global freshwater fish species loss, we also convert regional impacts into global comparable impacts using global extinction probabilities (Kuipers et al., 2019).

2. Materials and methods

2.1. Calculation of characterization factors

The Characterization factor (CF) modeling in this study includes the influence of GHG emissions on short- and long-wave radiation, global air temperature and water discharge, the subsequent influence on river water temperature and finally the effects on freshwater fish species (Fig. 1). The modelling approach for the changing river water temperature is coming from 2 different models (i.e., Barbarossa et al., 2021; Pachauri et al., 2014).

In this study, we only focus on the impact of increasing water temperature, although our used models predicted a reduced water temperatures in some regions (Fig. S1), such as South Asia. Liu et al. (2020) also confirmed that climate change can lead to a decrease in the water temperature of some rivers. In total, only 0.14 % of the assessed water temperature pixels showed a decrease in temperature (Table S1).

The here developed CF quantifies the fraction of freshwater fish species that are potentially affected due to a change in river temperature via the increase in GHG emissions (PAF·yr/kg), consisting of a Fate Factor (FF, ℃·yr/kg) and an Effect Factor (EF, PAF/℃), as shown in Eq. (1). The potentially *affected* fraction (PAF) based on acute data can be set equal to the potentially *disappeared* fraction (PDF) in LCIA (Raptis et al., 2017; Verones et al.,2010), thus the CF unit can also be indicated as PDF/°C for the lethal effect.

The CF is calculated for every GHG x for thermal effect e in every $5' \times 5'$ grid cell p under each climate scenario s and climate model m.

$$CF_{p,x,s,m,e} = FF_{p,x,s,m} \times EF_{p,s,m,c,e} \quad (1)$$

For the thermal effects e we considered sub-lethal and lethal effects. For climate scenario s we considered four Representative Concentration Pathways' Scenarios (RCP_s), namely RCP 2.6, 4.5, 6.0 and 8.5, and we used five Global Climate Models (GCMs) (i.e., GFDL, HadGem, IPSL, MIROC and NorESM) under each RCP scenario. Multiple GCMs are needed to account for the variability in model output resulting from different assumptions underlying GCMs (Warszawski et al., 2014). This can reduce the uncertainty of the climatic variables in the case of single

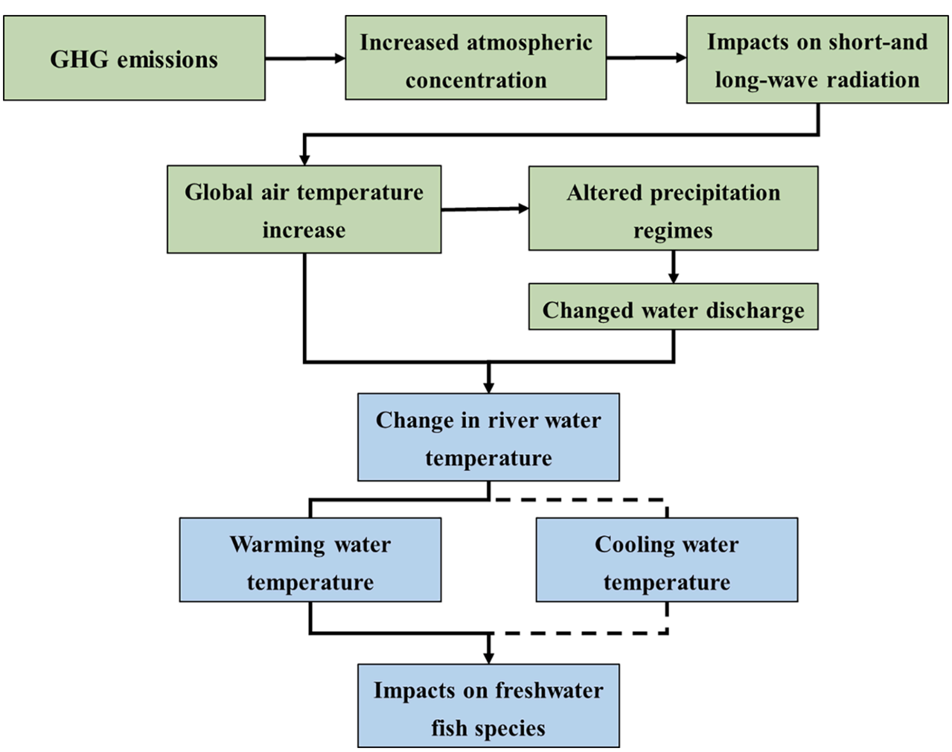

Fig. 1. The impact pathway of GHG emissions on freshwater fish species through river water temperature. Green boxes: combination models (i.e., climate model, hydrological model, water temperature model) deliver the changing water temperature. Dash line: pathway not considered in this study. The blue boxes and solid line mean the pathways considered in this study. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

GCM (Döll et al., 2016; Pachauri et al., 2014). The CF were calculated for 207 GHGs, as assessed in the IPCC fifth assessment report (Pachauri et al., 2014). Due to the amount of GHGs, we focus on the results of CO_2 in this manuscript while the results of the other 206 GHGs are presented in the Supporting information. For additional 4 GHGs (i.e., CH_4, N_2O, CF_4, HFC-125) also result maps are provided in the Supporting information 1 and other GHGs results are shown in Supporting information 2.

For the final CFs, the cell values are aggregated to the watershed level *r* (Eq. (2)), with *n* being the number of climate models and *z* being the number of grid cells within the watershed *r*.

$$CF_{x,s,e,r} = \sum\nolimits_{p=1}^{z\in r} \frac{\frac{\sum_{m=1}^{n} CF_{p,x,s,m,e}}{n}}{z} \tag{2}$$

2.2. Fate Factor calculations

The Fate Factor (FF) [℃·yr/kg] describes the change in river water temperature due to increase in GHG emissions (Eq.3).

$$FF_{p,x,s,m} = GWP_x \bullet \frac{\Delta T_{w,p,s,m}}{CO_2 - eq_s} \tag{3}$$

Where GWP_x is the global warming potentials of greenhouse gas *x* (kg·CO_2-eq/kg), CO_2-eq_s is the cumulative CO_2 equivalent emission in future scenario *s* (kg·CO_2-eq/yr). $\Delta T_{w,p,s,m}$ is the change in the water temperature T_w in grid cell *p* based on the outputs from climate model *m* under future scenario *s* (℃). The GWP_x, for a time horizons of 100 years and the cumulative CO_2 equivalent emission from 1980 to 2100 (Table S2) were extracted from the IPCC fifth assessment report (Pachauri et al., 2014).

$\Delta T_{w,p,s,m}$ is calculated as the difference between the global historical (average 1960–1979) and future (average 2081–2099) river water temperatures. We used the output of a global hydrological model (PCR-GLOBWB) fully coupled with a dynamic water temperature model (DynWat) at a spatial resolution of 5 arcminutes from Barbarossa et al. (2021). In total, global river temperatures changes were modeled for 20 GCM-RCP combinations.

2.3. Effect Factor calculations

The Effect Factor (EF) models the change of potential affected fraction (PAF) of freshwater fish species caused by increased river water temperature (Eq.4).

$$EF_{p,s,m,c,e} = \frac{\Delta PAF_{c,e}}{\Delta T_{w,p,s,m}} \tag{4}$$

Where $\Delta PAF_{c,e}$ is the average change in the potentially affected fraction of freshwater fish species in climate region *c* for thermal effect *e*. To obtain the three climate zones (i.e., temperate, sub-tropical and tropical), we reclassified a 30-sub-type climate map into four climate zones (i.e., polar and subpolar zone, temperate zone, subtropical zone and tropical zone) according to the classification provided by Meteoblue (Beck et al., 2018; Köppen, 1884; Meteoblue, 2020). We excluded the polar and subpolar zone during the calculations because we did not collect thermal tolerance data of fish species in this region.

To calculate $PAF_{c,e}$, we constructed six SSD curves, resulting from two thermal effects times three climate regions using a cumulative normal distribution function (De Vries et al., 2008). The average of thermal tolerance intervals value (μ_{TTI}) in each constructed SSD represented the TTI value that had a PAF of 0.5, as we used the normal distribution.

Similar to the FFs, the modeled EFs in this study are also based on an average approach because we are committed to calculate the predefined impacts set by society (e.g., RCP2.6, RCP4.5), compared with a reference state around 1980. The background state (Ta) and prospective future state (future water temperature and cumulative GHG emissions) are known. That is the reason why it is not consistent with the marginal approach from the studies on thermal pollution from power generation (Raptis et al., 2017; Verones et al., 2010).

2.4. Species sensitivity distribution

A Species Sensitivity Distribution (SSD) is a statistical distribution describing the sensitivity variation among a set of species for a specific stressor (Posthuma et al., 2001), and it has been commonly applied in risk assessment of toxicants (Del Signore et al., 2016), Life cycle impact assessment (LCIA) approaches regarding pH declines (Azevedo et al., 2015) and thermal changes (Verones et al., 2010).

Following De Vries et al. (2008), the PAF for the thermal effect *e* at the thermal tolerance interval (TTI) can be calculated with Eq.5.Where TTI_{CT} (Eq.6) and TTI_{LT} (Eq.7) are defined as the temperature for each species above the acclimation temperature (T_a) when reaching the the critical thermal maximum (CT_{max}) and lethal temperature (LT) (℃), respectively (De Vries et al., 2008).

CT_{max} is the thermal point at which an individual of a fish species loses equilibrium, and is regarded as the sub-lethal effect. LT is defined as the temperature at which 50 % of individuals die and this is used for the lethal effect (Becker and Genoway, 1979; Lutterschmidt and Hutchison, 1997) and ERF is the error function of the cumulative normal function.

$$PAF_e = \frac{1}{2}[1 + \mathrm{ERF}(\frac{TTI - \mu_{TTI_e}}{\sqrt{2}\sigma_{TTI_e}})] \tag{5}$$

$$TTI_{CT} = CT_{max} - T_a \tag{6}$$

$$TTI_{LT} = LT - T_a \tag{7}$$

A linear regression was used to derive the TTI for every effect *e* and each species *i* at each T_a (De Vries et al., 2008):

$$TTI_{i,e} = a_{i,e} \times T_{a,i} + b_{i,e} \tag{8}$$

where $a_{i,e}$ and $b_{i,e}$ are the slope and intercept, respectively. When there were multiple experimental data available for a single species, we included all the data to derive the regression coefficients. Following Moore et al. (2013), the coefficient of determination (R^2) greater than 0.5 and *p*-value less than 0.05 are considered as acceptable quality to ensure a reliable relationship between TTI and T_a.

Following (De Vries et al., 2008), $\mu_{TTI,e}$ is the average of the TTI (℃) for effect *e* (Eq. (9)), and $\sigma_{TTI,e}$ is the standard deviation (℃) for effect *e* *(Eq. (10))*.

$$\mu_{TTI_e} = \frac{1}{N}\sum_{i=1}^{N} a_{i,e} \bullet T_a + \frac{1}{N}\sum_{i=1}^{N} b_{i,e} = \mu_{a,e} \bullet T_a + \mu_{b,e} \tag{9}$$

$$\sigma_{TTI_e} = \sqrt{T_a^2\sigma_{a,e}^2 + \sigma_{b,e}^2 + \frac{2}{N-1}\sum_{i=1}^{N}(a_{i,e} - \mu_{a,e})(b_{i,e} - \mu_{b,e})} \tag{10}$$

Where N is the total number of fish species, $\mu_{a,e}$ and $\mu_{b,e}$ are the average regression coefficients $a_{i,e}$ and $b_{i,e}$, respectively, and $\sigma_{a,e}$ and $\sigma_{b,e}$ are the standard deviation of $a_{i,e}$ and $b_{i,e}$, respectively.

We used the average of water temperatures from five climate models as T_a because of the very small differences between model outputs (Table S3). Those were 12 ℃ in the temperate zone, 17 ℃ in the subtropical zone and 26 ℃ in the tropical zone. For the surplus temperature above the T_a, we used the difference between historical and future water temperature in every grid cell.

Since we used lab-based studies to assess impacts in the environment, we thereby assumed that acclimation temperature can be set equal to the average historical water temperature, as done in other LCA studies (Ankathi et al., 2019; Joensuu et al., 2021).

2.5. Data collection

To obtain experimental data of T_a, we used Web of Science and Google Scholar. More specifically, we searched for studies published until 2020 using the terms (freshwater fish*) AND (temperature or thermal or temp* or therm*) AND tolerance* in the topic field. Only studies that focused on thermal tolerance related to T_a were considered, thus studies reporting other experiments (for example, the effect of oxygen limitation or body size) were excluded. In addition, we obtained a comprehensive dataset from Comte and Olden (2017), which includes the quantitative estimates of the upper thermal limits of 2960 fish species in both marine and freshwater environments. Due to a lack of information in the collected studies, we did not differentiate between native and non-native species. We excluded species that only contained a single T_a and the corresponding thermal limit, because at least two points were required to identify a relationship. Data was collected for two thermal effects, namely sub-lethal and lethal effects. Fish species were assigned to a different climate zone (i.e., temperate, sub-tropical and tropical) based on the information retrieved from FishBase (Froese, 2009), since a comparison between thermal tolerances of fish communities in different climate regions was required (Payne et al., 2016). We reclassified a 30-sub-type climate map into four climate zones according to the classification provided by Meteoblue (Beck et al., 2018; Köppen, 1884; Meteoblue, 2020). We excluded the polar and subpolar zone during the calculations because we did not collect thermal tolerance data of fish species in this region. To compare the differences between life stages, collected fish species were also separated into juveniles and adults. For studies that did not report the growth stage of the experimental fish, we compared the observation information (total length) they provided with the maturity length criteria on FishBase to determine the growth stage (Froese and Binohlan, 2000).

2.6. Global application

To identify the contribution of regional freshwater fish species impacts to the global freshwater fish species impacts, the Global Extinction Probabilities (GEPs) were used in combination with the regional CFs (Dorber et al., 2020; Kuipers et al., 2019). The GEPs are conversion factors based on the size of the species' distribution area, IUCN threat category (to reflect existing vulnerabilities) and overall species richness, to translate fractions of potential regional species extinctions into potential global species extinctions.[33] In this study, we first aggregated the pixel-level GEPs of freshwater groups into watershed-level GEPs to correspond with the same spatial resolution. Then, the regional CFs for lethal effects were converted into global CFs by multiplying the regional CFs with the corresponding GEPs, to arrive at CFs representing global losses. Since sub-lethal effects do not entail the death and local extinction of a species, we cannot use the GEP for upscaling, thus sub-lethal effects remain at a regional level only.

3. Results

3.1. Species sensitivity distribution

Our literature search resulted in 328 articles, of which 125 studies contained information for 182 fish species related to sub-lethal effects and 67 studies for 123 fish species related to lethal effects. 63 species had data for both effects available. 136 studies were discarded because they reported experiments that were irrelevant for our purpose. The average and standard deviation of the regression coefficients at a given T_a and the collected numbers of fish species in every category are shown in Table 1. The regression coefficients were different between climate regions and between sub-lethal and lethal effects. Detailed information for each fish species are available in Fig. S2 and Tables S4–S6.

Almost all the sample points used to construct the 6 SSDs curves were laying within the 95 % confidence interval (Fig. 2). All regression coefficients were significant (p-values < 0.05) and R^2 were all above 0.9. This can indicate that SSDs presented here are robust to present the relationship between potentially affected fraction of species (PAF) and thermal tolerance interval (TTI). As expected, the SSDs differed between the three climate regions, and the average of the TTI (μ_{TTI}) for lethal effects was higher than that for sub-lethal effects at the same T_a, because fish species had higher temperature interval before death than equilibrium loss. The TTI causing a 50 % potential disappearance of species was the lowest in tropical zones and the highest in temperate zones for both sub-lethal effect and lethal effects ($\mu_{trop} < \mu_{sub} < \mu_{temp}$), while the variability in TTI (σ_{TTI}) was consistent in all three climate regions. The trends of SSD curves in tropical zones were much steeper in comparison to those in temperate and sub-tropical zones. The freshwater fish species in the tropics were more susceptible to a greater percentage of potential disappearances.

Table 1
The average values and standard deviation of regression parameters for freshwater fish from three climate regions and for sub-lethal and lethal effects, as well as the number of species included in the regression.

Sub-lethal effect		*a*		*b*		Number
Zones	T_a	*u*	*σ*	*u*	*σ*	
Temperate	12.14	−0.687	0.167	25.176	3.510	64
Sub-tropical	16.86	−0.622	0.145	26.316	4.027	73
Tropical	25.98	−0.695	0.165	31.152	4.361	56
Lethal effect		*a*		*b*		Number
Zones	T_a	*u*	*σ*	*u*	*σ*	
Temperate	12.14	−0.732	0.144	26.610	4.250	53
Sub-tropical	16.86	−0.683	0.155	28.333	5.049	53
Tropical	25.98	−0.773	0.133	33.597	4.051	17

3.2. Fate factors

For the pixels with increasing water temperature, all RCP scenarios showed similar spatial distribution for the FF, with FFs generally being higher in the tropical regions of South America, the temperate regions of North America and southern Europe because of the larger increases in water temperature (Fig. 3). The differences between maximum and minimum FF values were for to five orders of magnitude. The FFs for CO_2 varied between 10^{-15} and 10^{-19} °C·yr/kg with a median value of 10^{-16} °C·yr/kg. The FFs of the other GHGs were 10–10,000 times larger than those for CO_2, reflecting their potential impact on water temperature in comparison to CO_2. A list of the FF ranges for the five main GHGs is presented in Figs. S3-S7 and Table S7.

3.3. Effect factors

The EFs of warming water temperature for sub-lethal effect and lethal effect ranged from 10^{-6} to 10^{-2} PAF/°C and 10^{-6} to 10^{-2} PDF/°C, respectively (Fig. 4). The EFs were generally higher for the pixels in the tropical zones and at the higher emission scenarios for both sub-lethal and lethal effects. The EFs for the tropical zone were the largest, one to two orders of magnitude higher compared to the EFs of the other zones (Table S8).

3.4. Pixel-level characterization factors

The pixel-level CFs for CO_2 are presented in Fig. 5 and for the other four main GHGs in Figs. S8-S11. All GHGs show the same patterns, since the CFs for the other GHGs are linearly scaled (with a multiplying factor) based on FFs for CO_2. Impacts for tropical freshwater fish species were the largest, followed by sub-tropical fish species and temperate fish species. Generally, higher emission scenarios resulted in larger impacts on freshwater fish, which is especially evident in the tropics. The differences between maximum and minimum pixel-level CFs were five to six orders of magnitude (see also Table S9). This indicates that the

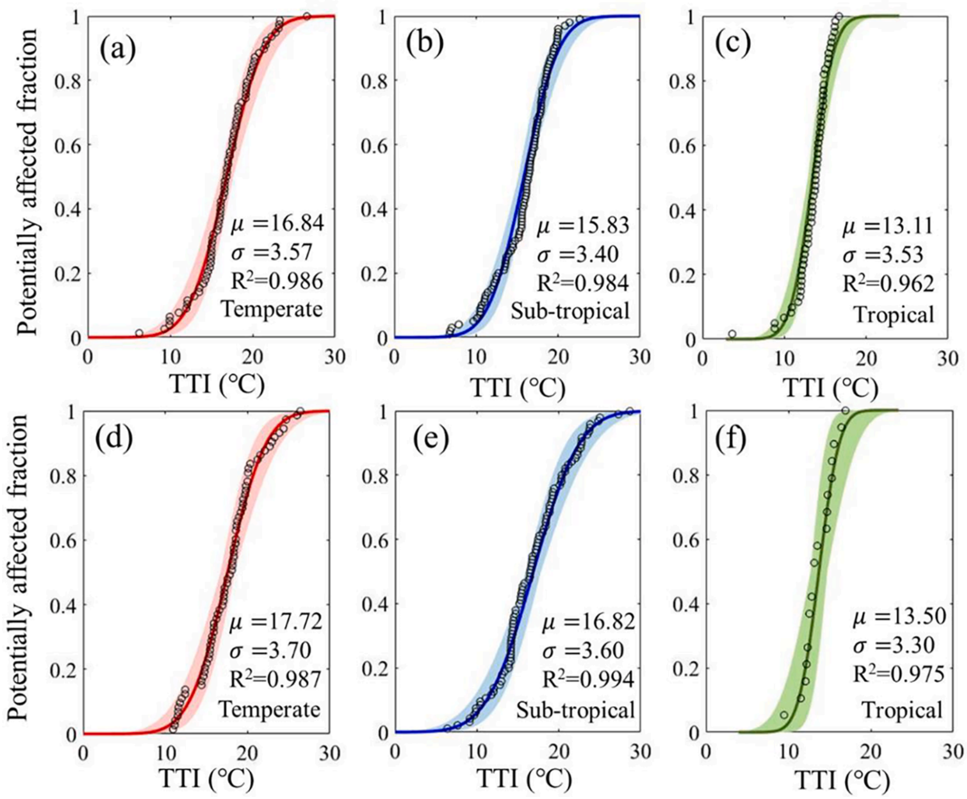

Fig. 2. The SSD curves for three climate regions and two thermal effects: (a)-(c) for sub-lethal effect and (d)-(e) for lethal effect. Colors represent the different climate zones: red = temperate zone, blue = sub-tropical zone and green = tropical zone. Shaded area: 95 % confidence intervals for the SSD. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

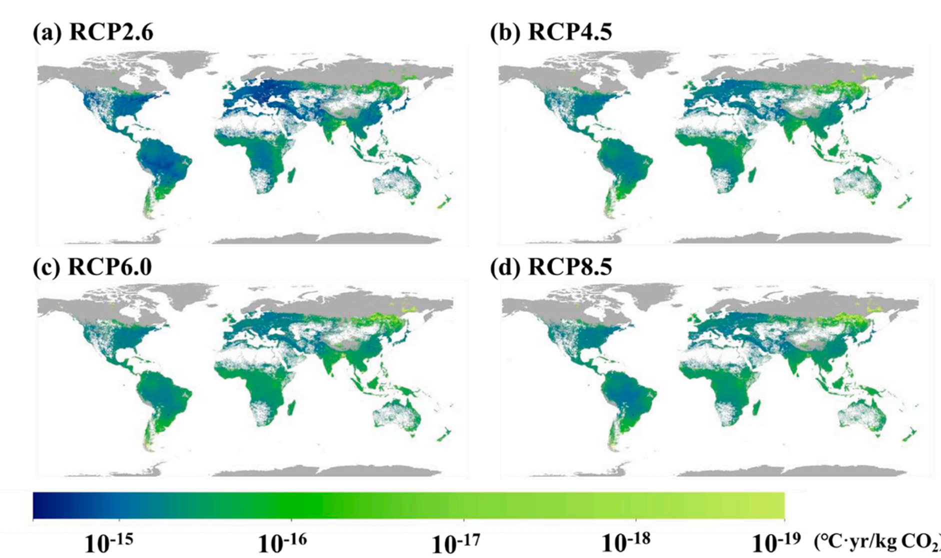

Fig. 3. FFs maps at 5 arcminute level for CO_2 for (a) RCP 2.6, (b)RCP 4.5, (c) RCP 6.0 and (d) RCP 8.5. The grey areas and white areas are also not included for FF maps, meaning no modeled increasing water temperature data.

responses of ecosystem quality towards global warming impacts can vary substantially. Our CFs of CO_2 for lethal effects vary between 1.98×10^{-22} and 4.58×10^{-18} PDF·yr/kg. They were lower than the CFs of between 1.25×10^{-16} and 8.34×10^{-16} PDF·yr/kg reported by Hanafiah et al. (2011). Correspondingly, this also holds for the other GHGs.

3.5. *Watershed-level characterization factors*

The watershed-level CFs were aggregated based on the pixel-level CFs (Fig. 6 for CO_2, Maps of the other four main GHGs can be found in Figs. S12-S15). The differences between the maximum and minimum values of the watershed-level CFs were three to four orders of magnitude (Table S10). The CFs for CO_2 ranged from 2.91×10^{-22} to 6.53×10^{-18} PAF·yr/kg for sub-lethal effects and from 1.98×10^{-22} to 4.58×10^{-18}

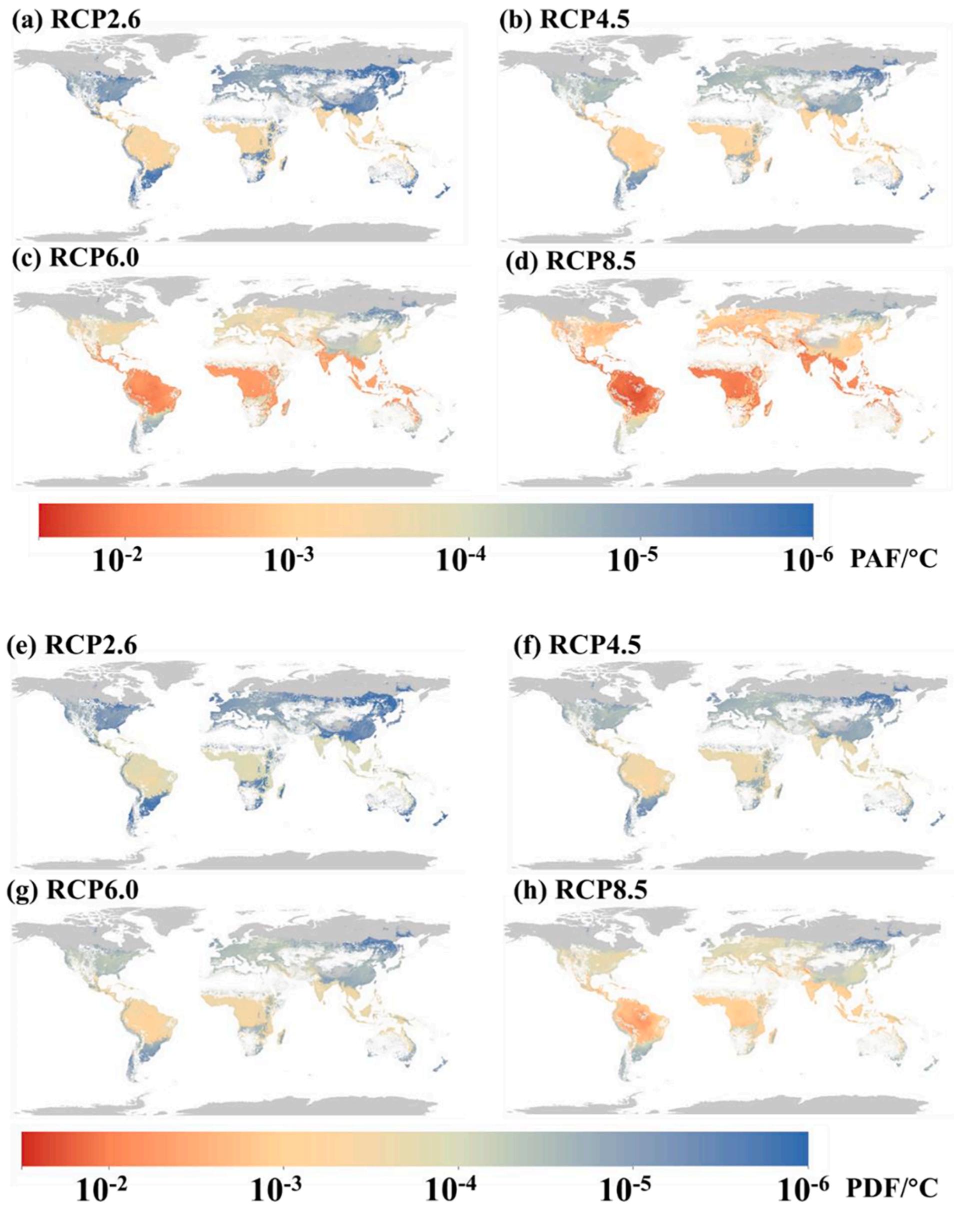

Fig. 4. The EFs maps at 5 arcminute level for sub-lethal effect (a-d) and for lethal effect (e-h).

PDF·yr/kg for lethal effects, depending on the watersheds and future climate scenarios. Consistent with pixel-level CFs, the highest level of global warming (RCP8.5) resulted in the largest CFs and the largest CFs occurred in the tropical watersheds.

3.6. Global impacts

All RCP scenarios showed similar spatial patterns (Fig. 7 and Figs. S16-S19), and a complete overview of the CFs for the global impacts of all 207 GHGs can be found in SI-2. Compared with the regional CFs, the differences between maximum and minimum values of global CFs were larger (9–11 orders of magnitude).

Analogous to the regional impacts, GHG emissions impacts on the tropical watersheds showed the greatest impacts for global freshwater fish species diversity under the four future scenarios. The top three watersheds with the greatest contribution to global freshwater fish species impacts were the Amazon watershed, Zaire River watershed and Mekong River watershed.

4. Discussion

4.1. Species sensitivity distributions

The statistical parameters for lethal effects were higher than those for the freshwater vertebrates reported by De Vries et al. (2008) for LT_{50} with values of μ_a = -0.802 σ_a = 0.088 μ_b = 25.93℃ σ_b = 1.674℃. This is because of our larger sample size (n = 123 for lethal effect) in comparison to their dataset (n = 29). In addition, De Vries and colleagues did not take climate zones into account. Also, our study included a broader range of fish species to improve the confidence of freshwater fish response to thermal. However, since we need two data points per thermal experiment for each species to establish the relationship we have a lower species coverage tan for example Comte and Olden (2017) (n = 327).

The SSD curves of three climate regions have similar variability in TTI (σ_{TTI}) but the smallest average in TTI (μ_{trop}) for tropical region, indicating that a higher proportion of tropical fish are potentially affected by unit increased water temperatures. Our findings are in accordance with the statement from Nati et al. (2021) that tropical fish

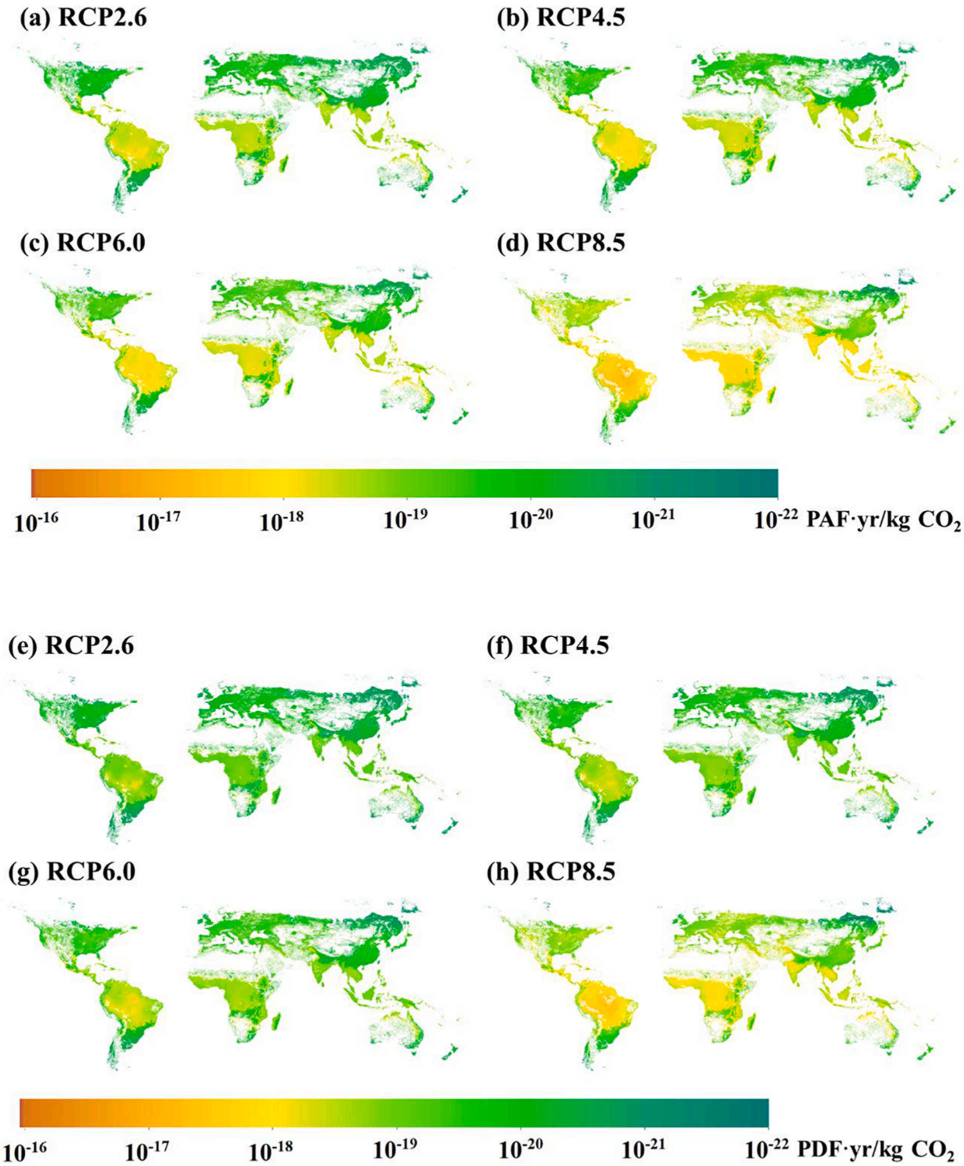

Fig. 5. The CFs map of CO_2 at pixel level for sub-lethal effect (a-d) and lethal effect (e-h) for a 100-year time horizon.

species may have higher sensitivity and lower adaptability to global warming. Therefore future studies should focus on refining the spatial and temporal detail of this model (once more data becomes available) to yield more accurate SSDs (Pfister and Suh, 2015).

4.2. Fate factors

Despite the consistent maxima and minima ranges, a variability of interquartile range and median between GCMs was found, with higher values for HadGem, IPSL and MIROC models than for GFDL and NorESM models (Fig. S20). We also noticed some extreme values (defined as the values beyond the 1.5* interquartile range) in every GCM, which drove the large magnitude difference of FFs. These outliers accounted for about 2 % of the total number of pixels (Table S11). These variabilities of FFs were mainly attributed to the uncertainties of water temperature outputs from GCMs, which was similar to the simulations of hydro-climatic variables reported by Greve et al. (2018). The heterogeneity in hydraulic characteristics and boundary conditions can be likely main factors (Yearsley, 2012). In addition, we recognized that the response of water temperature to all GHGs emissions is a nonlinear feedback process. The FFs for RCP 2.6 were significantly higher than those for the other RCPs. This is mainly related to the zero or even negative emissions required in the RCP 2.6 scenario, which is the only pathway that limits global warming below 2℃ (Collins et al., 2013).

4.3. Effect factors

A larger increase in water temperature generally results in larger EFs in the tropics. But more importantly, the EFs are strongly dependent on the thermal sensitivity of the present freshwater fish in each climate zones. For example, when the water temperature increases by 1 ℃, the EF for sub-lethal effects in the tropical zone is calculated to be two orders of magnitude higher than the EF in temperate and sub-tropical zones. The higher EFs in the tropics are mainly caused by the more sensitive SSDs, as previously discussed in Species Sensitivity Distribution part. Besides, the high emissions level (RCP 8.5) also resulted in one to two orders of magnitude higher EFs, compared with the low emissions level (RCP 2.6).

In addition to the commonly reported lethal effect in LCA, this study also provides new EFs based on sub-lethal effects. Accounting for sub-lethal effects helps shedding light on the potential destabilizing effect of warming waters on fish communities.

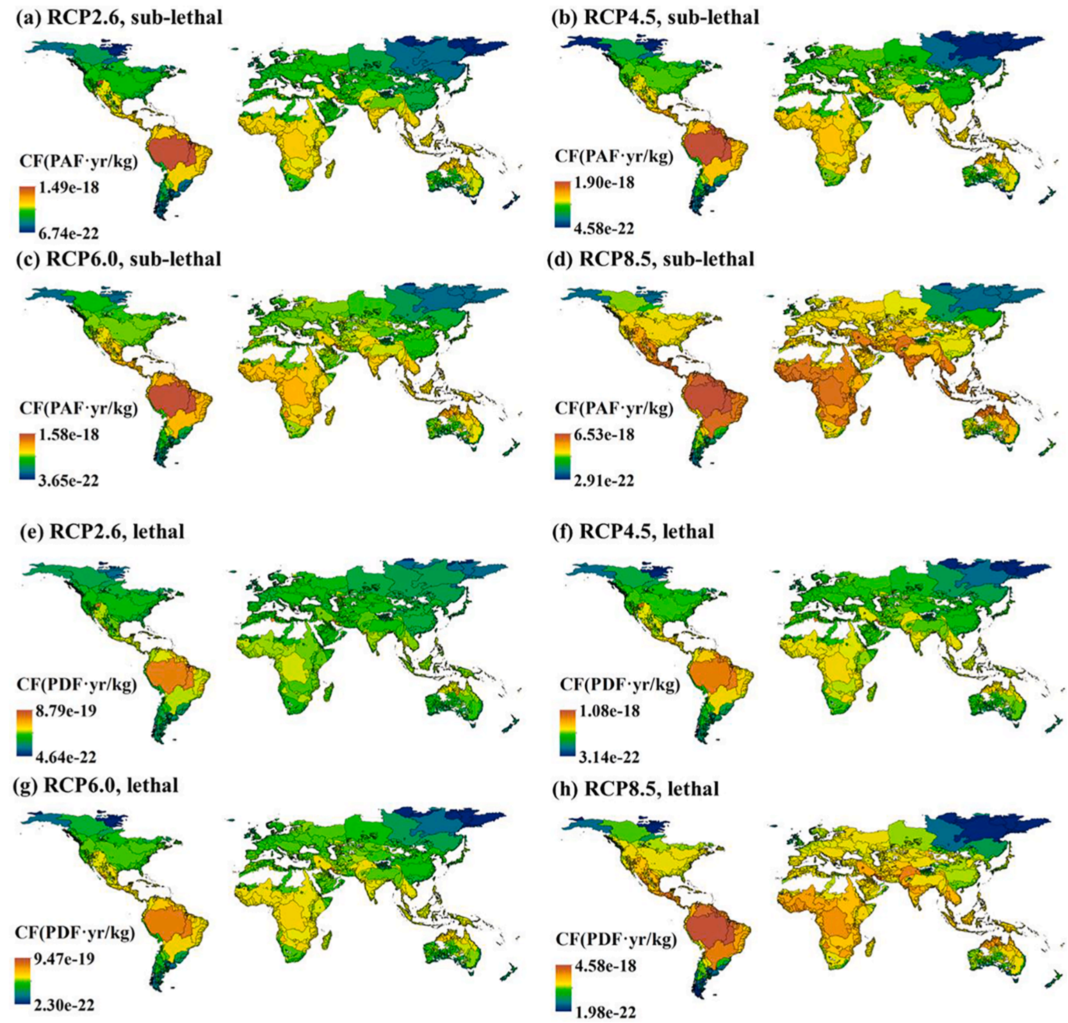

Fig. 6. The watershed-level CF maps of CO_2 of four RCP scenarios for sub-lethal (a-d) and lethal effects (e-h).

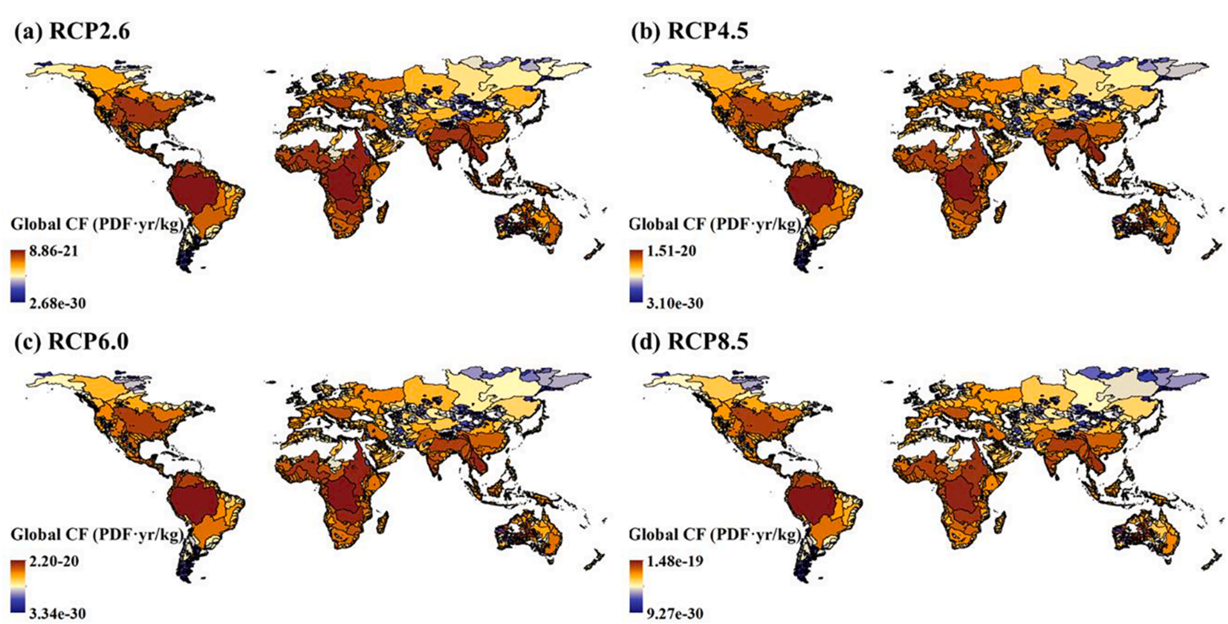

Fig. 7. The global impacts for CO_2 on freshwater fish species at watershed level for four RCPs.

The uncertainty of the EFs is mainly introduced in the application of the SSDs Because there is quite some variability in experimental conditions and procedures such as the heating rate between the different studies that we collected data from. Golovanov and Smirnov (2007) found that the largest differences between upper lethal temperatures could reach 10℃ at different water heating rates from 0.04℃/h to 50℃/h. The lack of standardization test conditions may trigger unconfirmed or dissimilar results (Azevedo et al., 2015; De Vries et al., 2008). Furthermore, we chose to integrate all the data to fit the regression line when multiple thermal limits results were available for individual species. Moreover, there is a spatial bias in the data availability of fish species. They are mainly concentrated in the Northern hemisphere and about 40 % are from the United States. This may affect the representativeness of the SSDs in the areas of the Southern hemisphere and therefore the results for tropical species might be more uncertain, especially for lethal effects (n = 17).

In addition, our SSDs do not differentiate the thermal tolerances between native species and exotic species. The exotic species tend to have a larger tolerance to environmental stressors (Fedorenkova et al., 2013; Leuven et al., 2011). The changes in water temperature may be favorable to these exotic species, which can lead to an indirect change in species composition (Verones et al., 2010).

4.4. Pixel-based characterization factors

The main reason for the difference of our results to the ones from Hanafiah et al. (2011) is the differences in the design of the cause-effect chain. We focus on the effects of GHG emissions on short-wave and long-wave radiation and the subsequent effects on water temperature, while Hanafiah et al. (2011) included the influence of GHG emissions on river water discharge. Dorber et al. (2019) and Gracey and Verones (2016) pointed out that multiple cause-effect pathways can lead to the same endpoint in an impact category. Global warming provides freshwater fish with changing environments through a number of mechanisms, not limited to one single impact pathway (Mohseni et al., 2003; Morgan et al., 2001; Poff and Allan, 1995). Our novelty is that we develop the new CFs for impacts of water temperature changes. Furthermore, the large range of our CFs (four orders of magnitude) is caused by the fact that we use three regional SSD models rather than one global species-discharge model as was the case in Hanafiah et al. (2011). In future research, a CF model related to climate change covering more impact pathways is needed, as insufficient dissolved oxygen contents, for example, may also lead to the suffocation of freshwater fish (Kramer, 1987). That will contribute to assess all the freshwater biodiversity impacts from global warming in Life cycle impact assessment (LCIA).

The impact category for climate change in current LCIA methods only contains global CFs considering its independence on the place of GHG emission (De Vries et al., 2008; Hanafiah et al., 2011; Verones et al., 2020). Our results highlight that it is equally important to introduce spatial differentiation in relation to climate change as is the case for other impact categories (e.g., water consumption). The differentiation into three climate regions is an important step for improving the accuracy of EFs related to water temperature changes in LCA. The updated SSD parameters (i.e., μ_a, μ_b, σ_a, σ_b) can also be used to further develop the EFs related to water temperature changes because of anthropogenic heat emission (Pfister and Suh, 2015; Raptis et al., 2017; Verones et al., 2010).

We provide CFs at both regional and global levels to quantify the lethal and sub-lethal impacts. We recommend using regional PDF for species richness loss and regional PAF for non-lethal impact of the relevant watershed in an LCA study. For the global impacts, the global PDF can be used to identify the potential global freshwater fish extinctions.

Our CFs operate on an annual basis and do not include seasonal aspects. However, due to differences in water temperatures between the seasons fish species are more likely to be stressed and at risk of extinction in summer than in winter. Verones et al. (2010) found for example higher EFs for impacts of water temperatures in summer than that in winter. However, adding a seasonality layer provides additional uncertainties in the application, since people would the need to know when they emitted a substance and this substance is likely going to be active over several years.

4.5. Watershed level and global characterization factors

The magnitude of CFs in tropical watersheds was almost one order of magnitude larger than that in temperate watersheds, underlining the importance of spatial differentiation in LCIA for global warming. This means that the threat to freshwater fish imposed by the global warming can be particularly serious in tropical watersheds, which is in accordance with the findings from Barbarossa et al. (2021) that tropical freshwater fish species are expected to be more affected by climate extremes. Among these watersheds, the Amazon watershed is expected to experience the greatest impacts by global warming.

Thermal limits data for polar freshwater fish species is currently not available, thus the aggregation of pixel-level CFs to a watershed-level unit introduces some uncertainties for polar watersheds. For watersheds partly located in the polar region, such as Norway, we can only average the pixel-level CFs in non-polar regions to derive the watershed-level CFs. Since the CFs in polar regions are expected to be lower, our aggregated CFs will lead to an overestimation in these regions. This uncertainty increases when the CFs are aggregated into a larger spatial unit such as countries. If appropriate data in polar region become available, our CFs should be updated.

The ranking of regional and global CFs was quite different. Some low-ranking watersheds for the regional CFs ranked high in the global CFs. For example, the Mississippi watershed ranked lower than 2000 in terms of regional freshwater fish species impact per kg GHG emissions for RCP8.5, but it ranked tenth for global species extinctions. This indicates that low regional impacts may still strongly contribute to global impacts due to regionally high presence of threatened species. On the other hand, relatively high regional impacts may not necessarily result in severe global extinctions, if mostly widespread and non-threatened species are present (Kuipers et al., 2019).

Our model addresses the impact of warming water temperatures on freshwater fish. However, there are other impacts that are connected to and influenced by global warming and all of them need spatial differentiation. Warmer temperatures lead for example to more evapotranspiration and potentially lower volumes of river water, as modelled in Hanafiah et al. (2011). On the other hand, there are also more indirect and cyclical connections, such as for example an increasing demand for irrigation water if temperatures are warming and this, in turn, can then lead to lower available water volumes in rivers and lakes, which warm up even more. With smaller water volumes available, dilution of pollution levels will also be smaller, meaning that in addition to impacts from warming temperatures and water consumption also impacts from toxicity or eutrophication could be exacerbated. LCA today, however, treats all impact categories as separate from each other. There is thus no interaction between impacts such as water consumption, global warming or eutrophication, even if these connections exist in reality.

5. Conclusion

Climate change is an important impact category in Life Cycle Impact Assessments. This study makes a step forward in modelling the impact of global warming on freshwater ecosystems by taking the local variation related to climate change into account. Our study clearly shows that spatial variation is an important aspect for this category, and we provide CFs at three spatial scales (global, watersheds and pixel level). In addition, this is to our knowledge the first study that provides factors for both lethal and sub-lethal impacts, indicate in potentially *disappeared* fractions of species and potentially *affected* fractions of species, respectively. Moreover, we provide CFs for both regional impacts and global extinctions. This makes our approach compatible with and relevant for the current efforts of the life cycle initiative hosted by UN Environment for furthering models related to global warming impacts and to provide factors in a compatible format as PDFs related to global extinction (Life Cycle Initiative, n.d.).

CRediT authorship contribution statement

Dan Li: Data curation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Martin Dorber:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Valerio Barbarossa:** Data curation, Writing – original draft, Writing – review & editing. **Francesca Verones:** Conceptualization, Methodology, Writing – original draft, 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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2022.109201.

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