Global water consumption impacts on riverine fish species richness in Life Cycle Assessment

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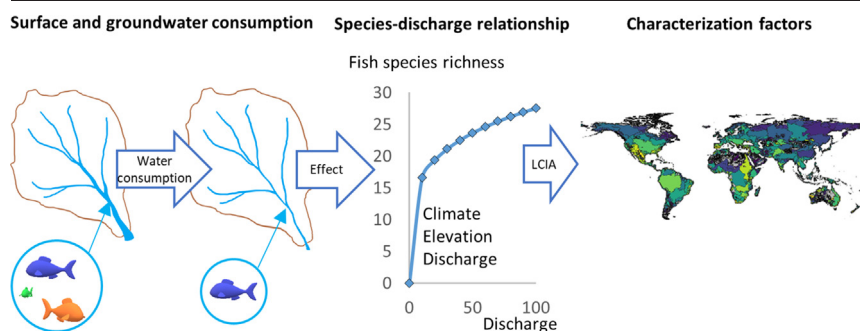[f] European Commission, Joint Research Centre, Via Enrico Fermi 2749, 21027 Ispra, VA, Italy
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HIGHLIGHTS

- We developed a model for assessing impacts of water consumption on riverine fish.
- Fish species richness losses are modeled by a species-discharge relationship.
- The new model has a higher spatial and fish species coverage than earlier ones.
- The model covers 3592 river basins and 11,450 riverine fish species.
- Water consumption potentially reduces species richness over 65 % of the river basins.

GRAPHICAL ABSTRACT

ABSTRACT

Reduced river discharge and flow regulation are significant threats to freshwater biodiversity. An accurate representation of potential damage of water consumption on freshwater biodiversity is required to quantify and compare the environmental impacts of global value chains. The effect of discharge reduction on fish species richness was previously modeled in life cycle impact assessment, but models were limited by the restricted geographical scope of underlying species-discharge relationships and the small number of species data. Here, we propose a model based on a novel regionalized species-discharge relationship (SDR). Our SDR-based model covers 88 % of the global landmass (2320 river basins worldwide excluding deserts and permanently frozen areas) and is based on a global dataset of 11,450 riverine fish species, simulated river discharge, elevation, and climate zones. We performed 10-fold cross-validation to select the best set of predictors and validated the obtained SDRs based on observed discharge data. Our model performed better than previous SDRs employed in life cycle impact assessment (Kling-Gupta efficiency coefficient about 4 times larger). We provide both marginal and average models with their uncertainty ranges for assessing scenarios of small and large-scale water consumption, respectively, and include regional and global species loss. We conducted an illustrative case study to showcase the method's applicability and highlight the differences with the currently used approach. Our models are useful for supporting sustainable water consumption and riverine fish biodiversity conservation decisions. They enable a more specific, reliable, and complete impact assessment by differentiating impacts

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on regional riverine fish species richness and irreversible global losses, including up-to-date species data, and providing spatially explicit values with high geographical coverage.

1. Introduction

A wide range of animal species are at risk of extinction (Ceballos et al., 2015). The Anthropocene is exacerbating impacts from various stressors on all ecosystems worldwide and freshwater ecosystems are at particular risk (Reid et al., 2019). Despite only covering about 0.01 % of the Earth's surface, freshwater ecosystems provide habitat for approximately 9.5 % of all globally recognized animal species (Balian et al., 2008). However, global freshwater species population size has declined by 84 % from 1970 to 2016 (WWF, 2020) and >30 % freshwater fish species are threatened with extinction (IUCN, 2022). In addition, global extinction rates of freshwater fishes were the highest among all vertebrates in the twentieth century (Burkhead, 2012). Reid et al. (2019) identified twelve key threats to freshwater biodiversity. Among these, flow modifications and changes in river discharge are recognized as persistent and well-known threats.

Water consumption from surface and groundwater has reduced river discharge (Wada et al., 2013) and therefore affect freshwater-dependent ecosystems (de Graaf et al., 2019). Water consumption is projected to increase globally due to urbanization, population growth, as well as increased needs for water in relation to industry and energy production (Piesse, 2020). There are options to reduce associated impacts, for example, with increased water use efficiency or water recycling. However, to make more sustainable decisions that do not lead to problem shifting (i.e., prioritizing choices that address a limited set of environmental issues without considering potential consequences on other aspects), methods that allow us to quantify impacts of water consumption on freshwater biodiversity should be in place.

Life Cycle Assessment (LCA) is an approach that allows quantifying environmental impacts of products and services to identify trade-offs between different impact categories (ISO, 2006). In the last decade, several Life Cycle Impact Assessment (LCIA) methods modeling the impacts from water consumption on in-stream species have been published (Damiani et al., 2021; Dorber et al., 2019; Hanafiah et al., 2011; Tendall et al., 2014). These LCIA models deliver characterization factors quantifying the potential damage to freshwater ecosystem quality per volume of water consumed. Among them, those quantifying the potential damage in terms of loss of species are based on species-discharge relationships (SDRs) and assume that there is a positive correlation between the number of fish species and the river discharge at the river mouth.

River discharge is a key variable in explaining differences in fish species richness (Hugueny et al., 2010; Iwasaki et al., 2012; McGarvey and Terra, 2016; Oberdorff et al., 1995). SDRs have been developed at different spatial scales, both regional (e.g. Xu et al., 2016) and global (e.g. Iwasaki et al., 2012; Oberdorff et al., 1995; Schipper and Barbarossa, 2022). Variations of the SDRs have also been investigated, which explain the residual variance of species richness using ecological hypotheses on habitat size and heterogeneity, energy availability, and evolutionary history (Oberdorff et al., 2011) or by clustering similar catchments (Dorber et al., 2019; Tendall et al., 2014).

Among the existing SDR-based LCIA models, Hanafiah et al. (2011) developed characterization factors for potentially disappeared fractions of species due to water consumption. They used one spatially generic SDR developed by Xenopoulos et al. (2005), including a limited number of basins (214) between 42° north and south. Building on this approach, Tendall et al. (2014) improved the effect modeling by regionalizing the SDR for fish species at finer spatial resolution, using a different regression function and accounting for species' threat status and rarity. This approach, however, limits the geographic scope to Europe, with a special focus on Switzerland. More recently, Dorber et al. (2019) developed SDRs and

characterization factors for Norway. All the above introduced models have in common that they used discharge flow as the only predictor for either global or regional SDRs, while other basin characteristics that may have an influence on species richness patterns at world scale, such as climate, climate history, and habitat heterogeneity (Oberdorff et al., 2011; Schipper and Barbarossa, 2022), were neglected.

In this study, we present novel characterization factors for LCA assessing water consumption impacts on freshwater ecosystem quality globally by developing an effect model based on a regionalized species-discharge relationship for riverine fish. We (i) developed globally-applicable SDRs that take into account the confounding effect of predictors other than discharge, (ii) derived regionalized characterization factors for impacts of water consumption on freshwater biodiversity, and (iii) tested their applicability on an illustrative case study. Our SDRs are calibrated on basin-level species richness estimates based on 11,450 fish species geographic distribution (Barbarossa et al., 2021), high-resolution simulated discharge flows (de Graaf et al., 2019), elevation, and climate zones, and cover 3592 river basins (88 % of the global landmass).

2. Method

2.1. Characterization factor framework

Our characterization factor represents the downstream impact of water consumption on freshwater ecosystem quality. The characterization factor is expressed in terms of the Potentially Disappeared Fraction of species (PDF), to ensure consistency across impact categories as recommended by the Life Cycle Initiative (Verones et al., 2017), per unit of water consumption rate ($m^3 \cdot yr^{-1}$, Eq. (1)). Therefore, multiplying the characterization factor with the water consumption associated with a product or a service provides an estimate of the potential damage to the freshwater ecosystem. The rationale behind our characterization factor is that water consumption can reduce streamflow, which in turn reduces the habitat extent of freshwater species, affecting their survival (Oberdorff et al., 2011; Poff et al., 2010). Thus, reduced flows might lead to the loss of species occurring within the basin affected by water consumption. Because the data availability is better than for other freshwater organisms, we focus on riverine fish only.

$$CF_{reg} = FF \cdot EF \; \left[PDF \cdot yr \cdot m^{-3} \right] \tag{1}$$

The fate and effect factors (FF and EF, respectively) represent how water consumption reduces river discharge (fate, Section 2.2) and subsequently lead to species loss (effect, Section 2.3) in a river basin. Therefore, the CF_{reg} represents the impact of water consumption on regional freshwater ecosystem quality in this specific basin.

By multiplying regional characterization factors (Eq. (1)) with an weighting factor called Global Extinction Probability (GEP) (Verones et al., 2022), we convert possibly reversible regional extinctions to potential irreversible global species extinctions. The Global Extinction Probability (dimensionless 0–1) represents the probability of species to go extinct globally if species disappear locally; thus, it is a proxy for the extinction risk of a species. The first step to obtaining the Global Extinction Probability for the fish group is to calculate the sum of the habitat area occupied by each species in a basin multiplied by the corresponding IUCN threat level (Categorical approach ranging from Least Concern to Critically Endangered). Second, this value is divided by the sum of the global occupied habitat area of all fish species. Third, each basin-scale value is divided by the sum of the threat levels for all present species. This procedure ensures that the sum of all basin-scale Global Extinction Probabilities for fish

species equals one. Therefore, if all fish species disappear in all regions, the fish species group will be extinct globally. Basins that contain a relatively high number of threatened species with a small range area will have comparably higher values. We obtain the global characterization factor CF_{glo} representing the impact of water consumption on global biodiversity with Eq. (2)

$$CF_{glo} = FF \cdot EF \cdot GEP \ [PDF \cdot yr \cdot m^{-3}] \qquad (2)$$

2.2. Fate factor

The fate of freshwater consumption is conceptually defined as the change of discharge at the river mouth due to upstream water consumption (Damiani et al., 2021, 2019; Dorber et al., 2019; Hanafiah et al., 2011; Tendall et al., 2014). We define the fate factor as shown in Eq. (3).

$$FF = \frac{dQ}{dWC} \qquad (3)$$

where dQ is the change of discharge at the river mouth corresponding to the increase of water consumption dWC in the river basin. Therefore, the fate factor is dimensionless. The fate factors were assumed to be equal to 1 in previous studies (Damiani et al., 2021; Hanafiah et al., 2011; Tendall et al., 2014), assuming that 1 $m^3 \cdot yr^{-1}$ of consumption causes 1 $m^3 \cdot yr^{-1}$ loss of discharge. However, this working assumption excluded all hydrological exchanges between rivers, aquifers, soil, and atmosphere, and the hydrogeological characteristics of the basin (de Graaf et al., 2019; Pierrat et al., in review) while future LCIA models for water use should include such exchanges (Núñez et al., 2018). Therefore, we used the Depletion Factors proposed by Pierrat et al. (in review) to derive fate factors for freshwater consumption including surface water exchanges with the atmosphere, groundwater, and soil. They are expressed in m^3 water availability change per m^3 water consumed that occurred between 1960 and 2000. Since the LCIA convention defines positive scores as negative environmental impacts, we define the fate factors as the opposite of Depletion Factors for discharge (Eq. (4)).

$$FF = -DF \qquad (4)$$

The Depletion Factors track the historical consequences of consumption on river discharge, groundwater storage, soil moisture, and evapotranspiration between 1960 and 2000 at the river basin scale, based on the outputs of the state-of-the-art Global Surface water Groundwater Model (GSGM) (de Graaf et al., 2019; Sutanudjaja et al., 2018). The GSGM models the vertical and lateral groundwater flows, which is essential to comprehensively represent the interactions between surface and groundwater (De Graaf and Stahl, 2022). In the case of river discharge, the depletion caused by consumption is derived from the difference between the simulated yearly average discharge at the river mouth, including all human interventions (i.e., human-modified water cycle), and the simulated discharge excluding all human interventions (i.e., natural baseline). Depletion factors are calculated for a 40-year period because the exchanges between surface water and groundwater are long-term hydrogeological processes. Thus, discharge Depletion Factors represent the cumulative change in river flow caused by the cumulative consumption volume expressed in m^3/m^3 from 1960 to 2000 in a basin. Negative and positive values indicate a loss and a gain of discharge caused by water consumption, respectively. We used discharge Depletion Factors to estimate fate factors (Eq. (4)), assuming that additional water consumption (dWC) has the same effect on the hydrological cycle as past water consumption (1960–2000).

Depletion factors for 8664 river basins were available (Pierrat et al., in review). We obtained positive fate factors in 7913 basins, corresponding to 74 % of the global landmass (excluding Greenland and Antarctica), where water consumption has historically reduced river discharge. In these basins, river discharge reduction can potentially damage freshwater biodiversity. The remaining 694 basins were flagged as "no discharge depletion" in the Support Material SM2 and no characterization factors are

provided there because the SDR approach should not be used to assess the impact of discharge increase on species richness (Xenopoulos and Lodge, 2006).

2.3. Effect factors

2.3.1. Deriving effect factors from the species discharge relationship

We derive marginal effect factors ($EF_{marginal}$) and average effect factors ($EF_{average}$) for each river basin, as recommended in the Global Guidance for Life Cycle Impact Assessment Indicators and Methods (UNEP/SETAC Life Cycle Initiative, 2016). They originate from the specie discharge relationship developed in this study (Fig. 1).

Marginal effect factors of water consumption are generally used for characterization approaches referring to "sufficiently small inventories that do not change the background situation" in the considered river basins (Forin et al., 2020). It is the case for most product LCAs as opposed to, e.g., large scale studies combining impact assessment and Multi-Regional Input-Output Models, where average characterization factors would be more appropriate (Forin et al., 2020). We stress that the definition of the threshold between marginal and non-marginal water consumption change, causing "small" and "large" discharge changes via the fate factor, cannot be made on a purely scientific basis and is always somewhat arbitrary. In this work, we follow the recommendation by (Boulay et al., 2020), who proposed a threshold of 5 % for the foreground water consumption change in a specific spatial unit to differentiate between marginal and non-marginal consumption patterns. This threshold was already applied within the water footprint method AWARE (Boulay et al., 2020), which is the consensus model recommended by the UNEP-SETAC Life Cycle Initiative for evaluating water scarcity related impacts of water consumption. Thus, the marginal and average effect factors are applicable for cases in which the foreground water consumption is respectively <5 % and ≥5 % of the river basin's total water consumption.

2.3.2. Marginal effect factors

Our marginal effect factor ($EF_{marginal}$ expressed in $PDF \cdot yr \cdot m^{-3}$) represents the loss of fish species richness due to a marginal change in discharge, whereby the latter is linked to the water consumption via the previously introduced fate factor. Thus, it was estimated using the slope of the response curve at the working point Q (Fig. 1) (Huijbregts et al., 2011). This definition was derived in analogy to Dorber et al. (2019), who quantified freshwater biodiversity impacts due to net water consumption of Norwegian hydropower reservoirs (Eq. (5)).

$$EF_{marginal} = \frac{1}{SR} \cdot \frac{dSR}{dQ} = \frac{1}{SDR(Q)} \cdot \frac{dSDR(Q)}{dQ} \qquad (5)$$

where SR refers to the riverine fish species richness, dSR to the loss of fish species, and dQ to the marginal discharge reduction at the river mouth
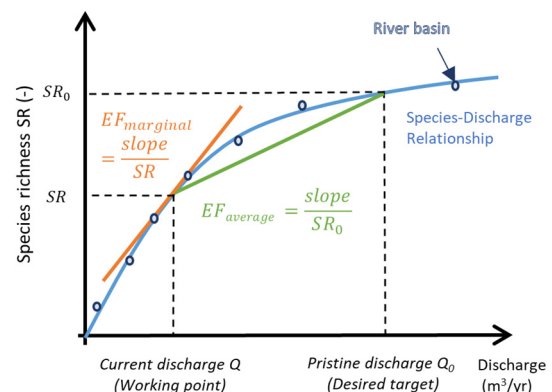

Fig. 1. Relationship between the potential loss of species, the species discharge relationship, and the effect factors.

$(m^3 \cdot yr^{-1})$. The marginal effect factor refers to the potentially disappeared fraction of fish species per m^3 water consumed over a time period in years $(PDF \cdot yr \cdot m^{-3})$. Previous SDR studies support the existence of a positive empirical correlation between discharge and fish species richness (McGarvey and Terra, 2016; Oberdorff et al., 1995; Schipper and Barbarossa, 2022; Xenopoulos et al., 2005), thus, marginal effect factors are always positive.

2.3.3. Average effect factors

The proposed average effect factor ($EF_{average}$ expressed in $PDF \cdot yr \cdot m^{-3}$) compares the species richness in the anthropized state (i.e. with water consumption) with the one in the pristine state (without consumption) (Huijbregts et al., 2011). It was estimated using the average slope of the SDR between the current discharge flow Q and the pristine discharge Q_0 (Fig. 1). The associated calculation is represented through Eq. (6).

$$EF_{average} = \frac{1}{Q - Q_0} \cdot \frac{SR - SR_0}{SR_0} \tag{6}$$

where Q_0 $(m^3 \cdot yr^{-1})$ and SR_0 are the annual discharge at the river mouth and species richness if there were no water consumption in the basin (natural simulation of the GSGM, see Section 2.2), Q $(m^3 \cdot yr^{-1})$ and SR are their respective counterparts when human consumption is considered. Similar to the marginal effect factor, the average effect factor represents the species richness loss ($SR-SR_0 < 0$) associated with discharge depletion ($Q-Q_0 < 0$), and is therefore always positive. Moreover, it is always inferior to the marginal effect factor in the same basin (see Figs. 1 and S8–9). To calculate SR_0, the species richness in the pristine state, we assume that the SDR is still valid for Q_0, then: $SR_0 = SDR(Q_0)$.

2.4. Species discharge relationship development

2.4.1. Spatial resolution

The native resolution of the characterization factors is defined at river basin scale, consistently with the underlying assumption of SDR models that basins are isolated ecological systems. Therefore, species richness in a river basin is driven by the hydro-geographic characteristics of the basin and evolutionary tendencies rather than species migration (Oberdorff et al., 2011). A basin is defined as an area draining to a common outlet (i.e., sea or internal sink). For consistency with the fate factors and the global extinction probabilities, we used the basin delineation derived from the GSGM. We also used the GSGM to derive the discharge corresponding to the basin delineation.

2.4.2. Geographical scope

Basins with null annual average discharge ($n = 738$) and unknown species richness were excluded ($n = 4884$). Moreover, small basins were excluded due to higher uncertainty on species richness. Species richness was derived from occurrence points assuming that the species is present in the watershed classification at level 12 (Hydroshed 12) (Schipper and Barbarossa, 2022). Species richness is uncertain in small river basins due to sampling bias and because some species could be misplaced when the basin is smaller than the base unit used for mapping the geographic ranges of the species (Barbarossa et al., 2021). Thus, basins with <2550 km² area (80th percentile) were excluded ($n = 16,254$) to reduce species richness uncertainty. As a result, we removed a total of 16,725 basins. The final dataset included 3592 basins, covering 88 % of the global landmass (the global landmass considered excludes Greenland and Antarctica). Details about the dataset sources, calculations, and scope map are available in the Supplementary Material 1, Table S1, Figs. S1–3.

2.4.3. Species and environmental data

Fish species richness in river basins is estimated based on 11,450 riverine fish species geographic distribution following the approach in Barbarossa et al. (2021). Non-native species were included in the study so that the SDR represents the current fish species richness' sensitivity to discharge. Non-native species have little influence on the overall species richness pattern as they represent <3 % of total species richness in 90 % of the river basins. Since fish species richness patterns are known to be influenced by a number of natural variables (Schipper and Barbarossa, 2022), we included the following variables in our initial model: mean annual discharge flow at the river mouth (Q in $m^3 \cdot s^{-1}$), elevation (E in m above sea level), slope (S in degrees), basin area (A in m^2), topographic index (TI, expressed as $ln\left(\frac{A}{tan\left(S\frac{\pi}{180}\right)}\right)$ and dimensionless), mean annual air temperature (T in K), mean annual precipitation (P in mm), air temperature change since the last glacial maximum (GLM) (ΔT expressed as $\frac{T_{present} - T_{GLM}}{T_{GLM}}$ in %), precipitation change since the last glacial maximum (ΔP expressed as $\frac{P_{present} - P_{GLM}}{P_{GLM}}$ in %). Additionally, broad geographic categories deemed as good proxies for several of these continuous variables were also considered. The advantage of using categories is that it may simplify the resulting SDR model by factorizing several continuous parameters in one single variable. We added the following categories representing habitat suitability, phylogenetic history, and energy hypothesis: freshwater major habitat types (Abell et al., 2008), biogeographic realms (Abell et al., 2008), and Köpper-Geiger climate zones (Beck et al., 2018). Categories were attributed to river basins based on the largest overlapping area. Additional information on the dataset is available in the Supplementary Material Table S1.

The continuous variables were averaged at the basin scale following the GSGM basin delineation, as commonly done in SDR studies (Oberdorff et al., 1995; Schipper and Barbarossa, 2022). We used time series of simulated monthly discharge from the GSGM to derive time series of annual discharge at the river mouth (Q). Then we calculated the annual average Q over the period 1970 to 2000 as the arithmetic mean of the annual values. The averaging smooths the inter-annual variability of discharge and the chosen period is consistent with the climate data (P and T). We also used the measured discharge from Global Streamflow Indices and Metadata archive (GSIM) to cross check if the use of simulated discharge affected the SDR model outcome (Do et al., 2018).

2.4.4. SDR modeling

We assume that the total species richness is in equilibrium with the long-term average environmental conditions in the river basin.(Oberdorff et al., 2011) Multi-linear regression models (MLM) were fitted to the log-transformed species richness. Among other potential predictors, we used the log-transformed discharge and the log-transformed area as previous SDR studies did (McGarvey and Terra, 2016; Oberdorff et al., 1995). Traditional linear models were preferred over other types of regressions because they result in a closed-form equation where coefficients are directly interpretable, which is necessary to derive characterization factors. Table 1 shows the five model candidates based on previous SDR literature (M1–M5). We investigated five models instead of one comprehensive model (M5) so that we could compare different approaches to SDRs found in literature. Because the river basin area can also influence the species richness positively, we added the log-transformed area of the river basin (logA) to the list of candidate variables for all models (Iwasaki et al., 2012; Oberdorff et al., 1995; Schipper and Barbarossa, 2022).

Ten-fold cross-validation was used to select the best model among the candidates (caret R package (Kuhn Max et al., 2021)). We used stratified splits of the dataset based on the major habitat type distribution because some of the habitats have few data points (Fig. S3). Such structured splits avoids extrapolation when fitting the models. For each model in Table 1 and each fold, the selected variables were automatically chosen among the candidate variables (dredge function from the R package MuMIn (Barton, 2022)), minimizing the Bayesian Information Criterion (BIC) (Table 1). We used the BIC to control for complexity because it gives higher penalty to complex models than the Akaike Information Criterion and we search for the most parsimonious model. After fitting each model for the ten folds, we selected the overall best model based on the lowest average BIC across the ten folds. This model was therefore selected to derive effect factors in this study.

Table 1

Model candidates of species-discharge relationships and literature underpinning.

Model name	Model justification	Candidate variables	Selected variables
M1	Species richness is a function of discharge (Oberdorff et al. 1995, Xenopoulos et al., 2005)	log Q	logQ
M2	Species richness is a function of available energy, habitat heterogeneity and evolutionary history (Oberdorff et al., 2011, Schipper and Barbarossa, 2022)	logQ, T, ΔP, ΔT, E, TI, S, log A	E, logA, logQ, ΔP, T
M3	Similar to M2 but habitat heterogeneity and evolutionary history are grouped by major habitat type/realm (Dorber et al., 2019; Tendall et al., 2014)	logQ, Habitat, Realm, logA	logQ, Habitat, logA
M4	In addition to discharge, latitude and elevation are the two gradients driving biodiversity (McGarvey and Terra, 2016)	logQ, Climate, E, logA	logQ, E, Climate, logA
M5	A combination of the above	logQ, T, ΔP, ΔT, E, TI, Slope, Climate, Habitat, Realm, logA	logQ, Habitat, ΔP, T

The form of the model for all candidates was logSR ~ f(logQ, candidate variables). LogSR: natural log-transformed fish species richness, logQ: natural log-transformed annual discharge at the river mouth, Habitat: the major habitat type in the basin, Climate: the Köppen Geiger 5 main climate zones, Realm: the geographical terrestrial realm.

The variables Mean Annual Precipitation was excluded upfront before fitting the models because it was deemed too correlated with log-transformed discharge (logQ) (Spearman rank coefficient > 0.70). The dredging function excluded the combinations of candidate variables which were considered collinear. Correlation between candidate variables was tested with the Spearman rank coefficient for continuous variables (excluded when $|rho| > 0.7$, see Table S2), the chi-square test on occurrence tables for categorical variables (excluded when p-value < 0.01), and the Kruskal-Wallis test for categorical and continuous variables. As a result, the exclusion rules removed the pair (T, ΔT) and one category could be included (Habitat, Climate, or Realm). Categorical variables and continuous variables pairs were all found significantly correlated, but no exclusion rules were applied because the strength of the interaction is not quantified and such rules would have excluded model M3 and M4 upfront. Moreover, the logQ was the only variable systematically included in all models and all first order interaction terms with logQ were included. In doing so, the coupled influence between discharge and other variables can be detected. A significant interaction between logQ and habitat type or climate zones would suggest that the influence of discharge flow on species richness depends on the geographical region.

In addition, we assessed to what extent the choice of simulated discharge over actual discharge measurements and spatial resolution of the basin boundaries affected our SDRs. To this end, we used an independent dataset from (Schipper and Barbarossa, 2022) with compiled species richness and discharge measurements (Do et al., 2018). We applied the model chosen in our study to the independent data and used the Kling Gupta Efficiency coefficient for comparison. Finally, to assess the improvement in accuracy of our approach, we compared our SDR model with the one previously used in LCA (Hanafiah et al., 2011).

2.5. Native resolution definition, geographical coverage, and aggregation

To enhance applicability of our characterization factors, we derived country-level characterization factors. These country values are useful when the river basin where extraction occurs is unknown. Following United Nations' Global Guidance on Environmental Life Cycle Impact Assessment Indicators recommendations for aggregation of characterization factors (Mutel et al., 2019), aggregated characterization factors at the country scale (UN, 2022) are obtained as the water consumption-weighted average of the basin scale characterization factors. The underlying assumption is that extraction is more likely to occur in regions where there is already significant water consumption. We adopted the annual average net water consumption in the river basin from 2005 to 2010 as weighting factor (Eq. (7)), so that the country average includes the most recent water consumption patterns. Indeed, water consumption has been accelerating since the year 2000 (Wada et al., 2016). However, the averaging period was constrained by the data availability from the GSGM (no data after 2010).

$$CF_j = \frac{\sum_k \frac{A_{k,j}}{A_k} WC_k \, CF_k}{\sum_k WC_k} \tag{7}$$

where CF_j (PDF·yr·m^{-3}) is the country j characterization factor, $A_{k,j}$ (m^2) is the area of the intersection of the basin k and the country j, A_k (m^2) the area of the basin k, WC_k (m^3·yr^{-1}) is the total net water consumption in basin k, CF_k (PDF·yr·m^{-3}) the characterization factor at the basin scale. However, some basins may have missing characterization factor values. This is because of two reasons. First, some basins do not present discharge decrease caused by consumption ("no discharge depletion" label in the Excel file Support Material SM2). These basins have no characterization factors because SDRs should not be used to assess the impact of discharge increase on species richness (Xenopoulos and Lodge, 2006). Second, other basins were excluded from the scope of our study because they were considered too small. To fill the missing values of these small basins, we defined a default characterization factors for each climate zone, according to the structure of our model (a different intercept is defined for the SDR depending on the climate zone). The default basin-scale characterization factor is equal to the combination of the median fate factor and the maximum effect factor in the climate zone. The basins with default values are flagged in the Supplementary Material (Excel file Support Material SM2). These small basins are assumed to have a small discharge flow, hence a high effect factor, and an average impact of water consumption on streamflow (median fate factor).

2.6. Application of the characterization factors to a case study

The aim of the illustrative case study was to test applicability of the newly developed characterization factors (CF$_{reg}$ and CF$_{glo}$), interpret their outcomes, and to compare the results to those of Hanafiah et al. (2011), which is part of the LCIA impact method "Recipe 2016" commonly used by LCA practitioners (Huijbregts et al., 2017). The latter is the precursor of the methodology we present here, and directly quantifies the damage to freshwater ecosystems from water consumption using fish species as proxies. It has though a narrower spatial extent (±42° lat.), fewer fish species covered, a regional fish damage assessment only (i.e., unknown contribution to global biodiversity loss), and a simpler (fate and effect) modeling approach.

We applied the developed characterization factors to an illustrative case study of rice cultivation in river basins producing 1 kg of rice within India, China, and USA. Irrigated agriculture, in particular rice cultivation, is a heavy water consumer, which can lead to water scarcity issues and impacts on freshwater biodiversity.

- India. Water basins: Ganges and Godavari
- China. Water basins: Yellow River and Pearl River
- US. Water basins: Red River and Arkansas River

Only water consumption for irrigation was considered in the assessment, which was 0.826 m^3 per kg rice in India, 0.487 m^3 per kg rice in China, and 0.835 m^{3}per kg rice in the US (Chapagain and Hoekstra, 2011). For each location, the impact was calculated by multiplying the water consumption and the river basin-specific characterization factors. Marginal characterization factors were used, since the water consumption to produce 1 kg rice is small (i.e., <5 %) relative to the water consumption by all activities in the basin (see Section 2.6).

3. Results and discussion

3.1. Selected species-discharge relationship model

Models M5 and M4 performed better than the other models, i.e., they reported lower BIC (M5: 10113, M4: 10252) and higher Kling Gupta Efficiency coefficient (M5 mean: 0.71, sd: 0.026; M4 mean: 0.69, sd: 0.022) after running the cross-validation procedure (Tables SM3–4). However, habitat type coefficients in M5 were not all statistically significant ($p > 0.1$) and this variable bears more uncertainty than the climate zone variable in M4 because a river is less likely to host a single habitat type than climate zone, thus M4 was deemed the best model to develop effect factors (see equations in Tables 1 and S4).

The regression coefficients reflected two large-scale biodiversity gradients, namely latitude and elevation. Climate zones in the selected model are built on precipitation and temperature data, which are strongly related to latitude. Moreover, empirical studies of terrestrial species distribution show that species richness changes with past and present climate (Araújo and Peterson, 2012), which suggests that climate zones are also relevant for freshwater fish species distribution. The intercept values associated with climate zones at lower latitudes (e.g., tropical, temperate), hence warmer and wetter basins, show higher species richness than basins at higher latitudes (e.g., Polar, Cold) (Table 2). A notable exception is the arid climate zone, which had the lowest average fish species richness despite relatively low latitudes (e.g., in the Sahara Desert). Possible explanations are the small extent of water bodies in these regions and the prevalence of intermittent streams, whose biodiversity is sensitive to prolonged drying (Leigh and Datry, 2017; Messager et al., 2021). As expected, the regression coefficients comparison showed that elevation negatively influences species richness while discharge and area influences were positive (Oberdorff et al., 2011; Schipper and Barbarossa, 2022). The hypothesis explaining the elevation gradient is that high-altitude river basins are more isolated and have lower primary productivity, thus a lower species richness (Rahbek, 1995). Besides, higher species richness is found in large basins and with high discharge because both are proxies for freshwater habitat size (Hugueny et al., 2010). Even though area and discharge are correlated (Spearman rank coefficient = 0.4), the mechanisms by which each factor influences the species richness are not equivalent. Discharge is also a proxy for the available energy in the river basin, while basin size co-varies with speciation rates, extinction rates and habitat heterogeneity (Hugueny et al., 2010; Oberdorff et al., 2011). Dominance analysis of the coefficients show that climate zones is the most important parameter to predict species richness (R^2 average contribution: 14 %–36 %), then discharge (R^2 average contribution: 9 %–25 %), followed by area (R^2 average contribution: 1 %–3 %) and finally elevation with (R^2 average contribution: 1 %–4 %) (Table S9). M4 showed a better goodness of fit than M1, thus M4 reflects the influence of the discharge on species richness better by considering climate and elevation explicitly compared to traditional SDR models that include only discharge. Finally, the selected model M4 does not contain interaction terms, which indicates that, on a log scale, discharge has the same influence on species richness in each climate zone,

in contrast with McGarvey and Terra (2016), where the interaction between latitude and discharge was found significant.

When testing the selected model robustness on 315 basins between 42° north and south, with observed discharge measurements (GSIM dataset) instead of simulated values, the overall goodness of fit decreased as the Kling Gupta Efficiency coefficient (0.56) dropped by 25 % (residual variance + 3 %, and correlation coefficient −30 %). In comparison, the Kling Gupta Efficiency coefficient of the SDR model currently in use for characterization factors (Hanafiah et al., 2011) had a lower performance than our model (Kling Gupta Efficiency coefficient = 0.13, all goodness of fit indicators are reported in Table S5 and plots in Fig. S10). Most improvement in goodness of fit using our model stems from the bias ratio, which means that the selected model predicts better average species richness, probably because our study includes updated and more comprehensive species data (11,450 species) (Barbarossa et al., 2021, 2020).

The regression coefficient of the logQ (0.20) was found to be two times smaller in our model than the SDR developed in Xenopoulos et al. (2005) that was previously used for calculating characterization factors in LCA (Hanafiah et al., 2011). Nevertheless, our estimate is consistent with the slope range estimated in different regions of Europe (0.06–0.45), but 26 % lower than the European average estimate (0.30) (Tendall et al., 2014). Therefore, including additional variables (climate, elevation, area) to describe the species richness beyond the sole discharge has reduced the latter's overall influence in the SDR by removing the influence of confounding variables. This may also be due to the correlation between discharge and climate zone, which may lead to underestimating the discharge regression coefficient. Nevertheless, reduced logQ slope is consistent with a study on an Island Species-Area Relationship (ISAR) which explored the correlations between slope and intercept in such models (Matthews et al., 2019). Island Species-Area Relationship models predict species richness as a power function of island area within a given archipelago in a similar way that SDR models predict freshwater species richness as a power function of river discharge. Drawing a parallel between SDR and Island Species-Area Relationship, the influence of the island area (river discharge in our case) on species richness was found to decrease when the area and the scale of the archipelago (geographical coverage and number of basins in our case) and the intercept increase (additional variables). Therefore, the lower slope of the new SDR may be explained by the higher geographical coverage of our dataset and the inclusion of additional variables (elevation, climate zone) in the SDR compared to previous models (Hanafiah et al., 2011; Tendall et al., 2014).

Linear model assumptions, i.e., linearity, independence of residuals, homoscedasticity, normality of residuals, were checked visually on the residual plots (Fig. S4, observed vs simulated log species richness plot displayed Fig. S5). Post hoc verification was deemed satisfactory except for the independence of residuals hypothesis. The residuals are positive where species richness is low; thus, the selected model overestimates the species richness in these basins (e.g. arid climate zone). Conversely, residuals are slightly more often negative where species richness is high (e.g. tropical climate zone); thus, the selected model tends to underestimate the species richness there. This indicates that the model predicts medium species richness best. Moreover, spatial autocorrelation between residuals weighted by the inverse of the distance between basin centroids was found to be small (Moran I = 0.0232) though statistically significant ($p < 0.001$) (Table S6). Overall, the selected model was found to be robust enough and thus used to subsequently calculate effect factors for use in LCA.

3.2. Effect factors results

Updated effect factor formulas were obtained by inserting the model

Table 2
Regression coefficients for the best model (M4, Log SR ~ f(logQ, Climate, Elevation, logA)).

Covariate/predictor	Coefficient
Tropical	2.75 (2.46; 3.05)
Temperate	2.11 (1.70; 2.53)
Cold	1.29 (0.88; 1.70)
Arid	0.94 (0.52; 1.37)
Polar	0.50 (0.06; 0.93)
Elevation	$-2.00 \ 10^{-4}$ ($-2.40 \ 10^{-4}$; $-1.60 \ 10^{-4}$)
LogA	0.10 (0.06; 0.14)
Log Q	0.20 (0.18; 0.22)

The columns show the coefficients of the regression with predictors (not centered, not scaled). *P*-values for all coefficients are <0.001. 95 % confidence intervals are reported in parentheses after the estimate (CI2.5; CI97.5).

(Table 2) into Eqs. (5) and (6): $EF_{marginal} = \frac{a}{Q}$ (Eq. 8) and $EF_{average} = \frac{\left(\frac{Q}{Q_0}\right)^a - 1}{Q - Q_0}$ (Eq. 9, S4), where a is the regression coefficient of logQ, Q is the discharge, and Q_0 the discharge if there were no consumption in the river
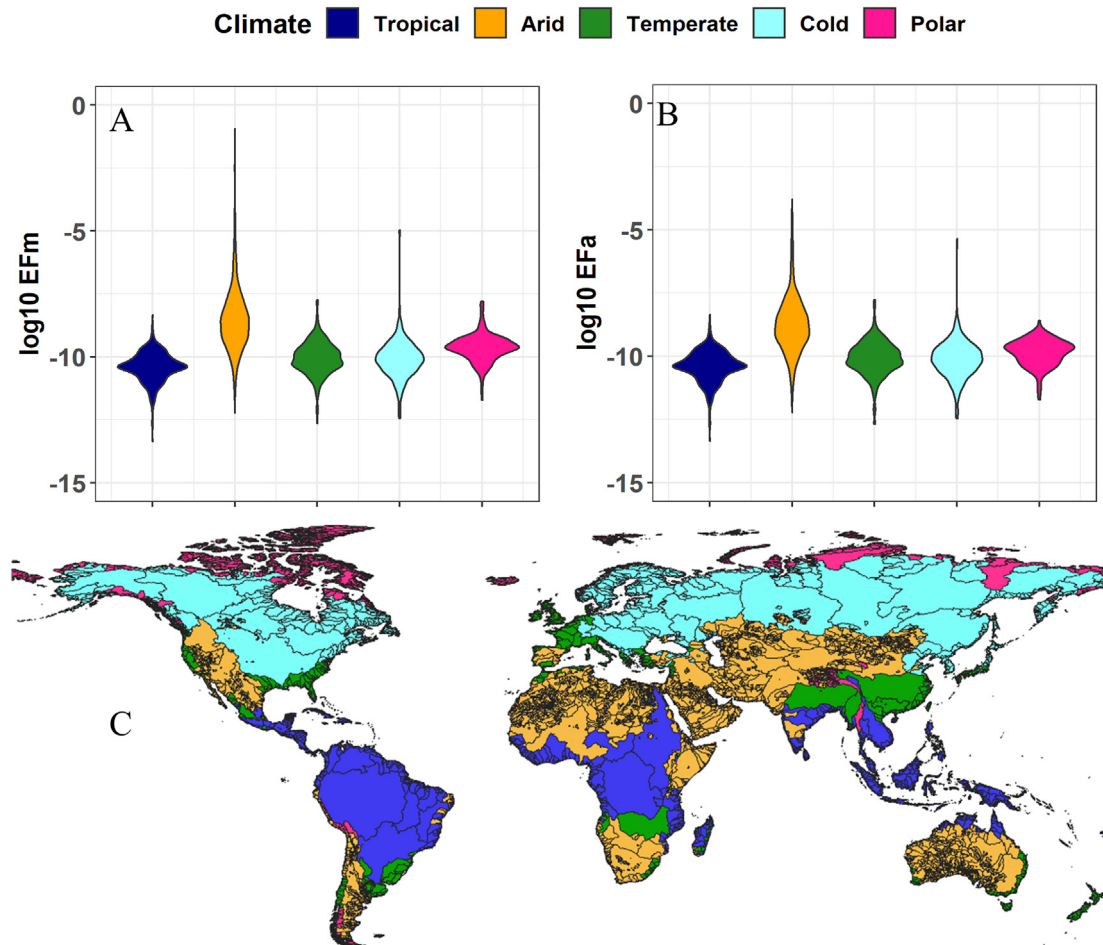
Fig. 2. Marginal (A) and average (B) effect factors at the basin scale in regional PDF·m^{-3}·yr in the different climate zones (C).

basin (more details in the Supplementary Material Section S3). Therefore, the regionalization of the SDR, i.e., the inclusion of additional variables in the model (see Eqs. S2 and S3), influenced the effect factors as much as it modified the coefficient a. In that sense, the developed SDR is midway between a bioclimatic envelope model and a species-discharge relationship (Araújo and Peterson, 2012). Interestingly, a was found constant across river basins, thus correcting logQ slope for each climate zone did not increase the model goodness of fit.

Marginal, regional effect factors (Fig. 2A) ranged from 3.93 10^{-14} to 0.10 PDF·yr·m^{-3}, and the distribution of average and marginal EFs are reported in Table S7. In four out of five emblematic rivers (Nile, Ganges, Yangtze, Euphrates, Amazon, Niger), marginal effect factors were on average 45 % lower than Hanafiah's characterization factors (PDF·yr·m^3·m^{-3}) divided by the river volume estimate (Table S8). The differences with Hanafiah's transformed characterization factors come from the discharge data and the basin delineation, which came from another global hydrological model (WaterGap 2, 2005 version). The order of magnitude of the marginal effect factors in the cold climate zone (median value: 6.85 10^{-11}) is consistent with Dorber et al.'s (2019) values for Norway (8 10^{-7}–7.10 10^{-12}). While Dorber et al. (2019) included the effect of the last glaciation on species richness by correcting the slope of the SDR, our model simply defines a smaller intercept in the Cold and Polar zones (Table 2) (Araújo and Peterson, 2012). Moreover, the new regional, marginal effect factors were overall higher in dry and polar climate zones due to lower discharge flow, and lower in tropical basins due to higher discharge flows (Fig. 2A). The bias in species richness estimates for low and high species richness may inflate EF in dry and polar climate zones, while underestimating the EF in tropical zones. A similar trend was observed for the regional, average effect factors (Fig. 2B), but slightly less dispersed in the Arid climate zone. The

regional, marginal effect factors are higher than the regional, average ones in 99 % of the basins, and the values are equal in the remaining 1 %, which was expected observing the slopes in Fig. 1. The ratio between average and marginal effects is generally close to one except in 10 % of the river basins where it is higher than 9 %. It corresponds to regions where the discharge has been heavily affected by water consumption. Further details about the statistical analysis and marginal and average effect factors are available in Table S7 and Fig. S6.

3.3. Spatial pattern of characterization factors

Four sets of characterization factors (marginal vs. average, regional biodiversity vs. global biodiversity) with their confidence intervals are reported in the Supporting Material Excel file SM2. We report the effect and characterization factors separately in SM2 to ensure the versatility of the effect factors, which are the core of our development. The aggregated characterization factors at country scale and global values (excluding all default values, see Section 2.4) are also available in this file.

Marginal characterization factors were calculated for both regional (Fig. 3A, n = 2350 basins) and global damages (Fig. 3A, n = 2320 basins) to freshwater fish biodiversity. The difference of geographical coverage between regional and global characterization factors comes from the combination of the fate and the effect factors and the Global Extinction Probabilities validity conditions (Sections 2.1, 2.2). We calculated similarly two sets of average characterization factors (characterization factor regional, global) (Fig. S6). In line with the effect factors, average characterization factors tend to be comparable to the marginal ones. The average impacts are smaller than marginal impacts in 100 % of the basins, in line with the effect factor tendency. This implies that any additional, small
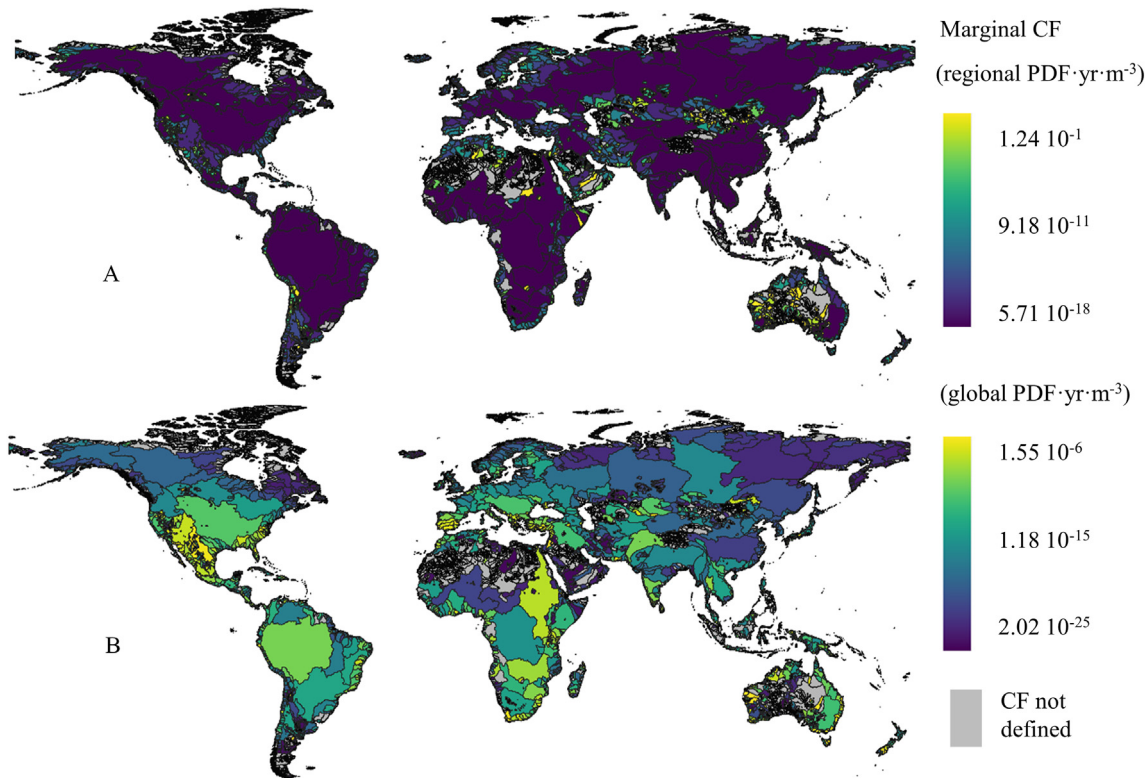
Fig. 3. Marginal characterization factors for impacts of water consumption on regional biodiversity (A) and global biodiversity (B).

water consumption nowadays is more likely to cause slightly more impacts than our average consumption in the past.

Higher characterization factors for regional species loss are especially found in smaller river basins in arid regions, such as North Africa, the Middle East, Central Asia, and Australia. This relates to the discharge influence on the effect factor (proportional to $1/Q$), see Updated effect factor formulas were obtained by inserting the model (Table 2) into Eqs. (5) and (6): $EF_{marginal} = \frac{a}{Q}$ (Eq. 8), causing small basins to have higher characterization factors than large ones. In contrast, higher characterization factors for global species loss are also found in larger basins, such as the Nile River in North Africa and the Colorado River and Rio Grande in North America.

Coherently, the effect factors contribute more to the variation in the resulting regional characterization factors than the fate factors. The effect factors exhibit a higher relative interquartile range and a higher Spearman rank correlation with the characterization factors (Tables S10 and S11). However, the Global Extinction Probability contributes the most to the variation in global characterization factors. These are, on average

(disregarding basins with zero global loss), seven orders of magnitude lower than for regional species loss. Such a large difference is expected, given that not all species that get lost regionally will go extinct globally. Both regional and global characterization factors are right-skewed, i.e. they have more lower values, which is consistent with the effect factors (Fig. 2A, B).

3.4. Case study application

The comparison reveals differences in the ranking of production systems across methods and differences in the span of results within each method (Fig. 4, Table S12). The results of applying Hanafiah and CF_{reg} differ particularly in India: with CF_{reg} producing 1 kg rice in Godavari river basin is markedly worse than producing it in the Ganges river basin, while with Hanafiah the impacts are higher in the Ganges river basin and the difference in impacts between the two basins are smaller (factor of 2 in Hanafiah vs factor of 11 in CF_{reg}). Although both methods employ
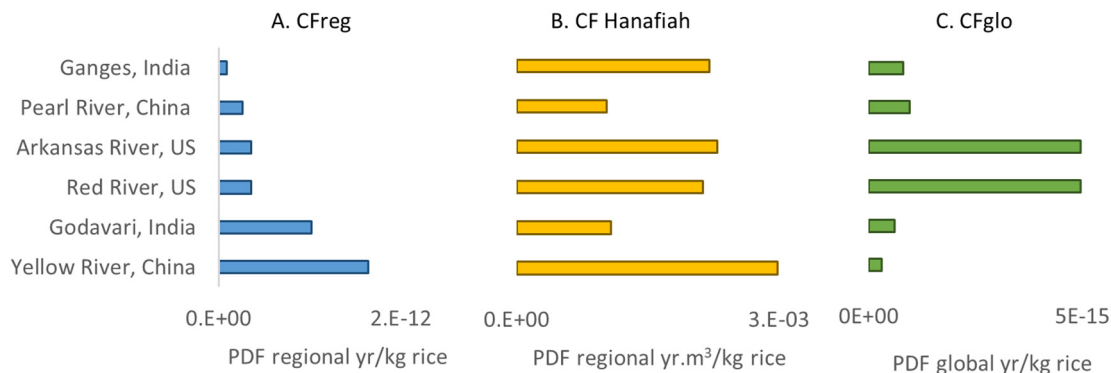

Fig. 4. Freshwater biodiversity impacts from water consumption per kilogram of cultivated rice in the three scenarios evaluated using: (A) the new characterization factors assessing regional biodiversity impacts (CF_{reg}), (B) Hanafiah et al. (2011), and (C) the new characterization factors assessing global biodiversity impacts (CF_{glo}).

SDR-based effect models in their characterization factors, there are many differences in the underlying models that explain the disagreement in the results. Contrary to Hanafiah et al., CF_{reg} is not weighted by the river volume, which renders an impact in a smaller river such as the Godavari River (river volume estimate 0.35 km^3) proportionally higher than in a larger river such as the Ganges River (river volume estimate 2.65 km^3). Therefore, the impacts calculated with CF_{reg} are consistently higher for smaller rivers than with Hanafiah in a given country (e.g., Godavari characterization factors are higher than Ganges characterization factors). Moreover, in Hanafiah, the fate factor was assumed to be always equal to one, while, in the new method, a consumption of 1 m^3 of water leads in the assessed locations to a depletion between 0.27 and 0.86 m^3 water in downstream surface water (Godavari fate factor = 0.40, Ganges fate factor = 0.34).

At present, the new LCIA method is the only one assessing impacts on freshwater biodiversity at regional and global scales (i.e., regional, and global PDFs), using CF_{glo} for the global assessment. Impacts on global biodiversity (Fig. 4C) are between two and three orders of magnitude smaller than impacts on regional biodiversity (Fig. 4A) for all basins, which is consistent with the regional and global characterization factors distribution (Section 3.3). Applying the global version would switch the hotspot, i.e., the basin with highest impact for a given method, from Godavari and Yellow River to Red River/Arkansas River as most impactful scenarios. This indicates that fish regional losses in the Red River/Arkansas River contribute more to global fish extinctions. Choosing CF_{glo} or CF_{reg} depends primarily on the objectives of the LCA, i.e. to protect local or global biodiversity, and if results should be aggregated or not. CF_{glo} improves comparability of damages to biodiversity across basins by taking the species distribution and threat level into account. Based on the new method, producing rice in the Ganges River or in the Pearl River appears to be the best compromise to minimize damages on regional and global biodiversity altogether. This conclusion is partially consistent with Hanafiah's method, where the lowest impact is in the Pearl River. However, rice should be produced in the Ganges River basin and Yellow River basin to minimize impacts on regional and global biodiversity respectively.

Overall, the ranking of the production systems depends on the location within a country, highlighting the importance of using river basin-specific characterization factors. For instance, there are basins with high and low impacts in China and India using CF_{reg} and Hanafiah et al.'s method. Rice irrigation water requirements vary between river basins too. However, this has not been considered here because of lack of data. If considered, the differences in the ranking between locations might have been larger. The span of impact results was one order of magnitude in Hanafiah et al.'s method and two orders of magnitude in the new method with CF_{reg} and CF_{glo}. Given the large characterization factors range of the new method, it shows a gain in the discriminatory power across locations as compared to Hanafiah et al.'s method. However, the effects of water efficiency improvement (i.e., reduction of irrigation water consumption per unit of product) on the basins ranking would have been more pronounced with Hanafiah et al.'s method, as, due to a shorter characterization factor span and equal fate factors both the Life Cycle Inventory and the characterization factor have a more balanced influence on the results. Both methods provide characterization factors for the locations assessed in the case study. However, the spatial detail of the new method is lower for the central US, where the areas producing rice are lumped together into the Mississippi basin that occupies over half of the surface of the country and where impacts of a unit of water consumption are thus considered to be the same. This is identified as a source of spatial uncertainty in impact results.

3.5. Limitations and future research

3.5.1. Uncertainty of characterization factors

Mutel et al. (2019) recommend distinguishing spatial variability from model uncertainty when providing spatially differentiated characterization factors. The parametric uncertainty at river basin scale depends on the uncertainty of the fate factors, effect factors and Global Extinction Probabilities. The uncertainty of the fate factors and the Global Extinction Probabilities are unknown, but a first estimate of confidence intervals of the characterization factors can be derived from the effect factor's confidence intervals thus reflecting SDR regression parameter uncertainty (Table 2). The lower estimate of the characterization factor is the combination of the fate factor with the lower bound of the effect factor confidence interval (CI5), and vice versa for the higher estimate of the characterization factor. The ratio of high to low characterization factor estimates is a rather small constant (1.14) and in line with the confidence intervals of the regression coefficients of the SDR (Table 2). Nevertheless, this range underplays the actual uncertainty of the characterization factors because we could not propagate all sources of uncertainty from the model and the data inputs due to a lack of information, e.g., uncertainties from the simulated discharge, estimated species richness and other data inputs, fate factors, Global Extinction Probability. Uncertainty ranges for country-scale characterization factor are derived from the combination of the lower and upper values of basin-scale characterization factor, respectively.

Moreover, we used simulated discharge from the GSGM to calculate the effect factor rather than measurements to maximize the geographical coverage of our model. Reliable measurement time series are not available for all river basins even in consolidated databases and tend to be biased towards large anthropized rivers (Krabbenhoft et al., 2022). Therefore, the use of simulated discharge data was necessary to avoid sampling bias. As a result, the effect factors are tied to the precision and accuracy of GSGM-simulated discharge, which has been extensively discussed in other studies (De Graaf et al., 2015, 2014; Sutanudjaja et al., 2014; Van Beek et al., 2011).

Finally, we used MLM with log-transformed species richness to develop our SDR as was done by (Dorber et al., 2019; Tendall et al., 2014; Xenopoulos et al., 2005). Other link functions (cumulative Weibull) or model types (e.g., Generalized Additive Models for Location, Scale and Shape) would possibly yield different goodness of fit indicators and possibly different regression coefficients. Nonetheless, the logarithm is relevant to removing the influence of scale from the model (Glazier, 2021) and testing the significance of the variables (Ives, 2015).

3.5.2. Limitations and research needs

In models where SDRs are used to estimate the presence of species in rivers and the potential loss of biodiversity associated with reduced river flow, discharge is interpreted as a proxy for habitat availability, analogous to species-area relationships for terrestrial ecosystems (Hugueny et al., 2010; Oberdorff et al., 2011). While this approach has the advantage of being relatively simple to apply, several studies have highlighted some limitations (Tedesco et al., 2013; Xenopoulos and Lodge, 2006).

The effect factor is not valid for representing the impact of increased discharge on species richness (Xenopoulos and Lodge, 2006), thus, no characterization factors are provided in these regions, and the model is not applicable for assessing the consequences of water release into the environment. Future studies should investigate how discharge increase would affect fish species richness and if the SDR can be adapted to reflect such effects, as recently done for emission of essential substances (Roibás-Rozas et al., 2022).

Species richness is generally associated with river flow via statistical regression, and the actual cause-effect relationship is more difficult to interpret (Yoshikawa et al., 2014). Therefore, this paper explores other explanatory variables of species richness in performing the regression analysis, selecting a seemingly more robust model than those based solely on river discharge. However, the causal relationship between decreased discharge at the river outlet and decreased species richness remains more difficult to investigate with the available data, and validation with empirical data would be necessary (Turgeon et al., 2021).

Another source of uncertainty concerns the choice of an indicator of species loss. Oberdorff et al. (2011) note that models based on SDRs return the fraction of species "committed to extinction" and that an actual extinction may occur over a period of time ranging from several tens to thousands of years. This uncertainty stems from the assumption that species occurrence is in equilibrium with hydrological conditions, which is often not the case (Olden et al., 2010). It is therefore necessary to investigate actual extinction

rates. It should be noted, therefore, that the indicator proposed in this article refers to a potential loss of species richness. For LCA application, it is common practice, as the currently recommended metric is precisely potentially disappeared fraction of species (Verones et al., 2017).

We selected the annual discharge as the most relevant hydrological parameter, while additional variables, which are related to discharge flow regime or area, may be associated with species extinction (McGarvey, 2014; McGarvey and Terra, 2016; Vander Vorste et al., 2017). These include additional descriptive variables of river flow in addition to magnitude (e.g., timing, duration), and connectivity. Nevertheless, average annual flow possesses good descriptive power to predict species richness and was found to explain equal or more variance of fish species richness than low flow, high flow, and flow seasonality for global scale modeling (Schipper and Barbarossa, 2022). Future research could focus on modeling the effect of flow variability and flow pulse timing alterations, which affect freshwater biodiversity through mechanisms that are not entirely covered by our model (Freeman et al., 2022; Poff and Zimmerman, 2010). For example, the river drying duration is a key determinant of freshwater macroinvertebrate biodiversity in intermittent streams (Leigh and Datry, 2017).

An additional factor to consider regarding the dependence of species richness on discharge is that the characteristics of assemblages are not considered nor are freshwater taxa other than riverine fish. In fact, specific traits and habitat preferences result in species responding differently to changes in hydrologic and hydraulic conditions. This factor can be taken into account by models that consider changes in community composition, including the establishment of non-native species, which might escape models based on species richness (Damiani et al., 2019; Turgeon et al., 2021). We limited our survey to riverine fish species because data are more complete and with global geographical coverage, while other freshwater species data, e.g., invertebrates, are scarce. Moreover, non-native species influence was considered negligible, as non-native species represent 3 % of the dataset used to develop the SDR. We also did not include lentic species, i.e., species living in standing water bodies due to lack of data.

Another important consideration relates to the dependency of SDRs on the scale. While considering water availability at the basin level allows the model to be applied to large-scale studies, such as those in life cycle assessment, it is important to note that, within basins, there is a longitudinal zonation and heterogeneity in habitat and species richness that determines basin-wide species diversity (Dunn and Paukert, 2021; McGarvey and Ward, 2008; Rolls et al., 2018). For instance, Schipper and Barbarossa (2022) found that climate is a more important predictor of fish species richness between rather than within basins, while the topographic index helped explain within basin patterns of fish species richness. For this reason, future research should consider the characteristics of species assemblages and regional freshwater habitats (Damiani et al., 2021) to improve the underlying models for damages to biodiversity in LCA.

4. Conclusions

We developed new LCA characterization factors for water consumption damage on riverine fishes for 3592 river basins. The effect factors and their confidence intervals were derived from a refined species-discharge relationship. This regionalized SDR was built on an up-to-date riverine fish species distribution dataset ($n = 11,450$) and covers 88 % of global landmass. The most parsimonious model included, besides discharge, climate zones and elevation as predictors, in line with the general expectation that macro-scale biodiversity patterns are well-described by latitudinal and elevation gradients (McGarvey and Terra, 2016).

The regionalized characterization factors enable more refined impact assessment by differentiating marginal and average impacts, and damages to regional (river basin-scale) and global biodiversity (4 sets of characterization factors), while previous methods only considered marginal regional impacts. Moreover, they feature higher discriminatory power, with a range spanning eight orders of magnitude as opposed to the two orders of magnitude of previous characterization factors (Hanafiah et al., 2011), likely resulting from a more accurate and comprehensive underlying SDR model.

In view of the fast degradation of freshwater ecosystems and increasing demand for freshwater resources, our characterization factors can support decision-making towards more sustainable systems and products by accounting for freshwater biodiversity impacts in Life Cycle Assessment.

CRediT authorship contribution statement

All authors have contributed to the conceptualization and methodology development. EP has developed the dataset, performed statistical analysis, calculated native-scale results, and prepared the visualizations. VB has provided part of the input data (species richness). MDo calculated aggregated characterization factors (e.g. country scale). MN performed the case study. LS did the formal analysis of the characterization factors. All authors have contributed to writing the original draft, review and editing. EP did the project management. MDo and VB did the supervision.

Data availability

The Supporting Material (SM1, SM2) including the characterization factors are available at DOI:10.11583/DTU.18549719. More data may be available upon request from the corresponding author. The data that support the findings of this study were derived from resources available in the public domain and in scientific literature as described in the methods.

The code used to preprocess, filter and model the data is available at: https://github.com/EleonorePS/Species-Discharge-Relationship.git.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.158702.

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