SUPPORTING INFORMATION FOR:

Seitfudem, G., Berger, M., Müller Schmied, H., Boulay, A.-B. (2025)
The updated and improved method for water scarcity impact assessment in LCA, AWARE2.0. *Journal of Industrial Ecology.*

Summary

This supporting information provides additional insight into the AWARE2.0 calculation process and an in-depth analysis of the different sensitivity scenarios as well as of the comparison to AWARE. It furthermore contains the case study of the Yellow River and China's CF and describes the process for aggregation of characterization factors to annual and country level and compares the aggregation to other LCIA indicators.

Contents

S 1 Methods

S 1.1 Large deltas – identification and calculation of CFs

Process for identification of large deltas (Figure S2) and their corresponding AWARE2.0 basins, based on the delta polygon dataset by (Edmonds et al. 2020) and conducted in QGIS and with a separate Python script. 50 major deltas were identified with the global dataset of Edmonds et al. (2020) (https://doi.org/10.1038/s41467-020-18531-4). A delta was classified as major if it i) covers at least the area of two grid cells and ii) intersects two basins. Corresponding basins were curated manually using satellite imagery from Google Earth Pro (Google LLC 2022) and the HydroRIVERS dataset v1.0 (Lehner and Grill 2013), available at https://www.hydrosheds.org/products/hydrorivers#downloads.

1. All delta polygons not intersecting any basin border (overlaying just one basin polygon) were discarded, which yields 563 delta polygons.
2. All remaining delta polygons were intersected with a vector dataset of the AWARE2.0 grid cells, dividing each delta polygon into snippets covering maximum one grid cell area.
3. The ratio of the area of each snippet to the land area of the covered grid cell was determined for every snippet. For each delta, the ratios were summed up in Python. Subsequently, the dataset was reduced to contain only deltas which had a sum of at least two, thus covering at least the area of two grid cells. This relatively complicated way of determining the area coverage is required because from the Equator towards the poles the size of grid cells decreases continuously. It was assumed that only continental area, and not ocean area was covered by the delta polygons.
4. The delta snippets were manually selected regarding their affiliation to AWARE2.0 basins depending on several conditions:
   a. If the snippet was very small, for example just a tiny corner of the delta polygon peeking into a grid cell for a few square kilometers, it was discarded. Using an algorithm only based on the size of the snippets was considered impractical as in some cases it would have discarded the main outflow cell of a basin.
   b. If one final grid cell combined two river flows coming in from different sides, the unification was not done, since in this case it would have also affected other basins which did not gain from the other river. This problem mainly appears in big bays with inflows from different sides (Pearl River, Amazon). A special case is the Rhine-Meuse delta, where in reality both streams merge approximately 5 grid cells away from the outflow to sea, but the GHM treats both as different watersheds up to the coast (see Figure S1, right). Therefore, both basins were merged. More complex deviations of the flow accumulation maps, if found, were not merged (see Figure S1, left).
5. For each basin, the corresponding delta and the main branch of that delta were identified.

The discharge to sea of all basins belonging to a delta was summed up and used as ActAvail for the calculation of the AMD. The same was done with the naturalized discharge which was used to calculate the EFR coefficient and EWR. As area, the sum of all individual delta basin areas was used. This way, the delta basins were essentially merged. However, the basin delineations were not changed, to avoid confusion about their IDs and a better comparability with AWARE. For the calculation of the $AMDworld\,avg$ every individual basin was weighted by its individual water consumption, which is the same as if all delta basins were considered as one entity and weighted by their combined total water consumption.

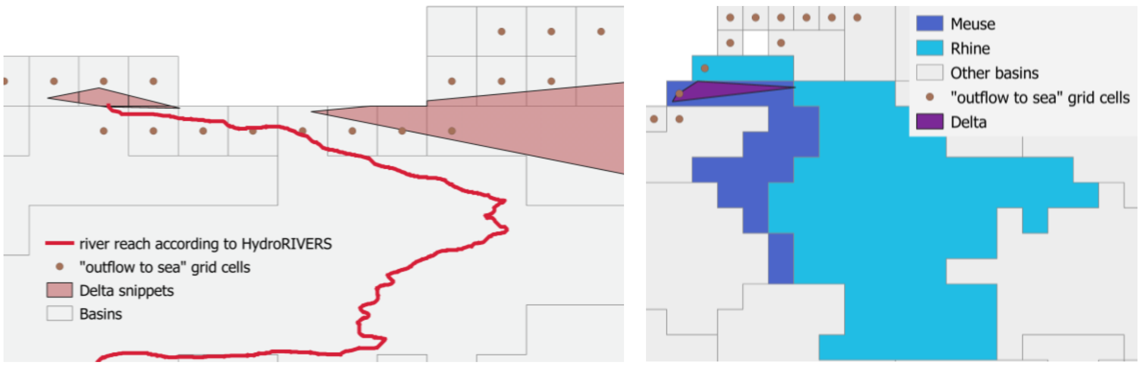

Figure S1: Left: Example of Olenyok River: Several grid cells are implemented as separate one-grid-cell basins, while the river reach in reality crosses them. The delta on the left therefore does not receive water from a large portion of its actual catchment area. Right: Example of Rhine-Meuse delta.

Figure S2: The 50 river deltas represented in AWARE2.0.

S 1.2 Subdivision of river basins

Table S1: River catchments subdivided in AWARE2.0.

Category	Name	
Discharge to sea	Amazon	Nelson River
	Amur	Niger
	Ganges	Nile

	Indus	Ob
	Jubba River	Oranje River
	Kongo River	Paraná River
	Lena	Shatt al-Arab
	Mackenzie River	Tocantins River
	Mississippi River	Yangtze River
	Murray River	Yenisey
Discharge to inland sinks	Aral Sea	Lake Eyre
	Lake Chad	Wolga
Desert watersheds	Libyan Desert	
	Saudi Arabian Desert	

S 1.2.1 Why subdivide river catchments into subbasins?

It is assumed that water consumption at a downstream river stretch can be expected not to influence water users far upstream. Consequentially, the calculation of a characterization factor for entire river catchments at once could overestimate the potential to deprive other users in the case of a consumption close to sea, while it could underestimate impacts of upstream users if water scarcity downstream is higher than upstream. In addition, tributaries joining to form a new river stretch do not influence each other's discharge. Water consumption in one tributary subbasin might not affect water availability in a "parallel" subbasin in case there are no water transfers in between the subbasins.

Another reason to subdivide large catchments is that water can require more than a month's time to flow through them. This means that upstream water consumption in a certain month could affect water availability downstream just several months later. Pfister & Bayer (2014) argue that therefore the spatial subdivision of large catchments should aim for subbasin-internal flow times of less than the temporal resolution of the factors. The subdivision of watersheds in AWARE in Boulay et al. (2018) does not consider this issue. This work uses the same subdivisions as AWARE because of lack of flow time data and to maintain consistency with the AWARE dataset.

S 1.2.2 The approach of Loubet et al. (2013)

Loubet et al. (2013) formulate an approach for the consideration of downstream effects of water consumption in upstream CFs: Weighting and adding up indicators along a chain of subbasins and dividing by a normalization value of the entire river catchment. The weighting, for example by area or population, is used to account for differences in the potential impact because of, for example, different numbers of humans affected. Loubet et al. use consumption-to-availability (CTA) ratios but also show how the approach would be applicable to indicators already containing a weighting factor in themselves. The approach satisfies two assumptions:

- No matter in which upstream subbasin a m3 of water is consumed, the effect on a given downstream subbasin will be the same. Therefore, the absolute contribution of water missing in this downstream subbasin to the LCA result will be the same.
- The average value of all CFs in a river catchment should be approximately the same as if there was no subdivision made for the catchment and therefore just one CF calculated.

The approach finally taken for AWARE2.0 deviates from these assumptions. The second assumption is not adopted since by subdivision the resolution of the CFs is increased intentionally, all *because* the spatial representativity of the CF without subdivision is doubted. The first assumption is satisfied just to a certain degree because of the assumption that an upstream deprivation potential cannot be decreased by lower deprivation potential downstream.

Even though area contributes to the AMD, the concept of AWARE does not consider area representing a proxy for population or vulnerability. The AMD as a whole is considered a basin-intrinsic property. To follow Loubet et al., another weighting factor would have to be used, e.g., water consumption. To proceed here is challenging though, since not every basin of AWARE is subdivided. Following Loubet et al. using a separate weighting factor would lead to unreasonable differences between subdivided and non-subdivided basins. The most downstream subbasin with the same AMD as a separate basin of the same size could receive a different AWARE factor than the independent basin, even if the variable used for weighting has the same value. This is illustrated in Figure S3.

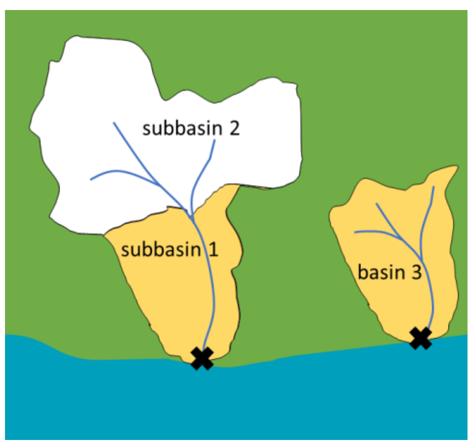

Figure S3: Two basins, the left one subdivided. Even with the same amount of water available per area, subbasin 1's AWARE CF could be different than the one of basin 3 when weighting for the subbasins is applied according to Loubet et al. (2013).

S 1.2.3 Approaches discussed for subdivision

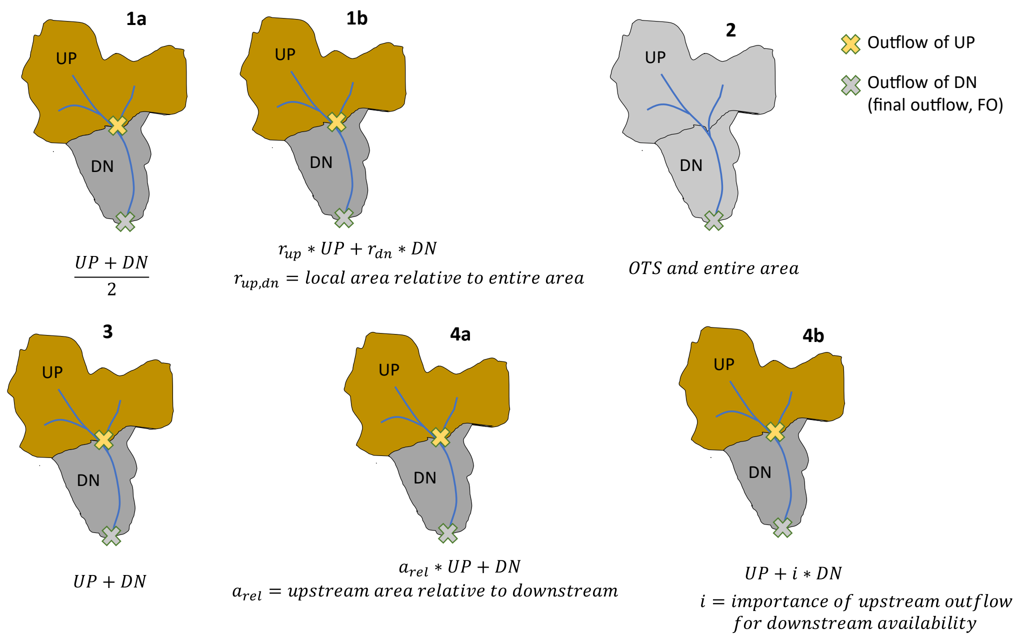

Figure S4: Subdivision of a basin in two subbasins (UP and DN) and mathematical options for including the potential deprivation of downstream users (DN) into the characterization factor of UP.

Figure S4 shows different ways to calculate the upstream final CF of local CFs or other variables. The six approaches shown are commented on in the following.

Approach 1a&b. Calculating averages. When consuming water in UP, the final potential to deprive users can be lower, the same, or higher than just locally in UP, because the water availability of DN alters it. If water scarcity is low in DN, this reduces the final UP CF. This contradicts the assumption that the deprivation potential cannot be lowered by high water availability downstream. One could define that the final UP CF is never lower than the local UP CF but increases if the DN CF is higher. Eventually, this approach comes close to adding up the CFs using a weight for one of them or both.

Approach 2. Final outflow and entire area. Using the final outflow as availability and the entire area as reference does not account for the fact that water availability upstream might be higher than downstream. However, it preserves the dynamic of increasing CFs with the movement upstream. It is an approach in line with the original idea of AWARE, which defines the CF as intrinsic basin characteristic, just influenced by water remaining at the outflow to sea and the area that this water is generated on.

Approach 3. Adding up the local CFs. This makes sense from the viewpoint that the m³ consumed upstream is missing in the upstream and the downstream basin alike (Loubet et al. 2013). It is like consuming the m³ in two separate basins at the same time, as long as the cut-off value is not reached by adding up both CFs. If adding up both local CFs leads to a higher value than 100, the CF would be cut off, so the LCA inventory will be multiplied by 100. Therefore, consuming 1 m³ each in two different watersheds whose CFs add up to more than 100 would lead to a higher result.

Approach 4a: Using the downstream basin as base CF and adding the upstream basin's CF based on its area relative to the downstream basin. This respects that both subbasins might be differently large and therefore a different number of users might be affected. However, if the upstream basin is much larger than the downstream basin, the final CF can be disproportionally large. Also, if the local CF of the upstream basin is high but its area small, the final CF could be smaller than the local CF, which is not intended. Using the upstream basin's local CF as base and adding the downstream local CF weighted by its area compared to upstream has the same effect of disproportional values if the areas are very different. Also, it could happen that the final CF is smaller than the CF of downstream.

Approach 4b: Using the dependency of the downstream subbasin on the inflow from upstream to weight its local CF when adding it to the upstream local CF. This would reflect that the upstream basin is less "guilty" of reducing availability in the downstream basin, if its inflow is just a small part of the entire input to the basin (other inflow from upstream and precipitation). For transport and dilution of issues like water pollution, this makes sense. For absolute amounts of missing water due to upstream water consumption, it is harder to justify, as the water *does not reach* the downstream subbasin (except if it is precipitated again as acknowledged for in WAVE and WAVE+ (Berger et al. 2014, 2018)).

S 1.2.4 Justification of approach 2

Approach 2 was selected, because:

- It is close to the general idea of AWARE (it can be understood as refining the spatial reference of the universal AWARE factor) and does not require additional input data
- It does not lead to a reduced comparability of subdivided and non-subdivided basins
- It does not require weighting or additional assumptions about links or relationships between individual subbasins
- The effect of a downstream subbasin on the LCA result is the same regardless of in which upstream basin the water is consumed (first assumption of Loubet et al. (2013)). This is because the AWARE CF is directly proportional to area
- Moving upstream, the CFs continuously increase, which is logical as more and more users are affected by the water consumption (first assumption of Loubet et al. (2013))

To satisfy the assumption that a local upstream deprivation potential cannot be decreased by impacts on downstream subbasins, the approach was adjusted. If a local CF is larger than the one calculated with approach 2, the local CF is used and the upstream subbasin's CF is changed accordingly.

The **main assumptions** required for approach 2 are that water consumption at some point of a large basin does not impact water users far upstream or in a parallel subbasin but impacts all water users downstream.

The first assumption is considered true for large basins, since the distances might not allow uphill water transfer or major water transfer in between subbasins. The second aspect is in line with Loubet et al. (2013) and can be considered true because 1 m³ consumed upstream will always miss in the downstream basin, except if:

a. a river runs dry and thus does not deliver water downstream
b. the water extracted is artificially transferred to the downstream basin
c. the absolute volume of water loss downstream (e.g., by evaporation) is highly sensitive to decreasing river volume
d. the consumed (evaporated) water precipitates in the downstream basin

It is assumed that condition a) is not relevant for AWARE, as no distinction is made where in a (sub)basin water is used, so a river reach in a downstream subbasin running dry does not affect AWARE factors. Furthermore, if a river runs dry in the upstream subbasin, its own local CF is probably already higher than the CF resulting from the subdivision approach and therefore could not be further increased by the downstream water availability. Condition b) is assumed to be irrelevant because of the distances in large basins and could be addressed by appropriate design of the LCA product system. Condition c) is irrelevant in case of marginal inventories in LCA, where it is unlikely that the river flow will be changed such that less evaporation occurs downstream. Condition d) is subject of research (Berger et al. 2014, 2018) but out of the scope of this study.

S 1.3 Interpolation of EFR coefficients

The interpolation of EFR coefficients for intermediate flows only affects a subset of all basins (Figure S5). Figure S6 shows the reason for interpolating: In some basins, the discrete jump in EFR coefficient (Table S2) leads to unreasonable discontinuities in the seasonal pattern of the EWR.

Table S2: Attributing environmental flow requirements (EFR coefficients) to hydrological seasons via flow intensity x (ratio of monthly to mean annual flow). ((Pastor et al. 2014), table modified from (Seitfudem 2022))

Flow intensity x	Hydrological season	EFR coefficient as fraction of monthly natural flow
$x \leq 0.4$	Low flow	0.6
$0.4 < x \leq 0.8$	Intermediate flow	0.45
$x > 0.8$	High flow	0.3

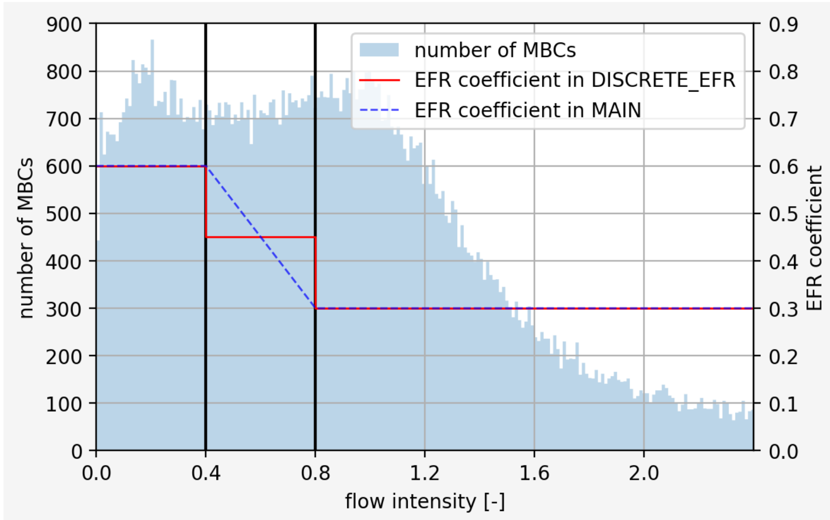

Figure S5: The interpolation of EFR coefficients based on the flow intensity between 0.4 and 0.8 compared to the constant value of 0.45. "MAIN" here is for AWARE2.0.

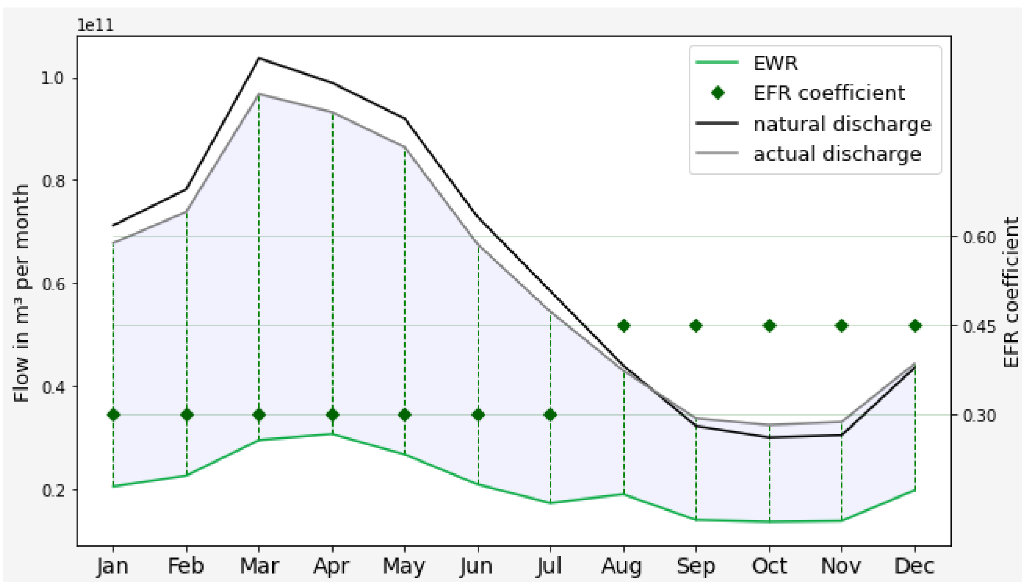

Figure S6: Mississippi basin: The jump in non-interpolated EFR coefficient leads to a sudden increase in EWR for the month of August, compared to July.

S 1.4 Additional information on covered basins

From AWARE to AWARE2.0, 798 basins have a different extent in AWARE2.0 or do not exist anymore, due to different classification of grid cells as land or sea in the GHM data (Figure S7). In AWARE, factors were not provided for all basins of the publicly available vector file. For some, this was because of missing data, whereas basins in Greenland were masked because of low reliability of the GHM output in this region (Müller Schmied et al. 2014; Seitfudem 2022). AWARE2.0 follows the approach of discarding certain basins because of low confidence in their results and therefore only includes basins which have a land area of more than 1% of their grid cell area (to account for the mismatch of GHM resolution and represented area, see also Wood et al. (2011)) and where less than half of their grid cells is ice-covered. The latter is to account for lack of calibration of WaterGAP2.2e output in polar regions (Müller Schmied et al. 2014, 2024) and for the limited meaning of the AMD based on liquid river discharge in subzero-degrees. To smoothen the dataset, 8 isolated Arctic watersheds are removed manually. It was shown before that the exclusion does not influence CFs of the remaining basins since the excluded basins represent a negligible part of the global water consumption used for weighting (<0.001%) and therefore have limited influence on the $AMD_{world\ average}$ (Seitfudem 2022). It however increases the robustness of the statistical analyses and interpretation of the dataset, because only relevant basins (not ice-covered, with water consumption) with higher confidence in the GHM result are assessed (Boulay et al. 2021; Müller Schmied et al. 2021) and it reduces the use of CFs from regions without GHM calibration. Figure S8 shows the basins included in the analyses of AWARE2.0.

Figure S7: Basins with reduced grid cell number in AWARE2.0 compared to AWARE. If the basin consisted of just one grid cell, it does not exist anymore in AWARE2.0 (e.g., the 120 “basins” of the Caspian Sea).

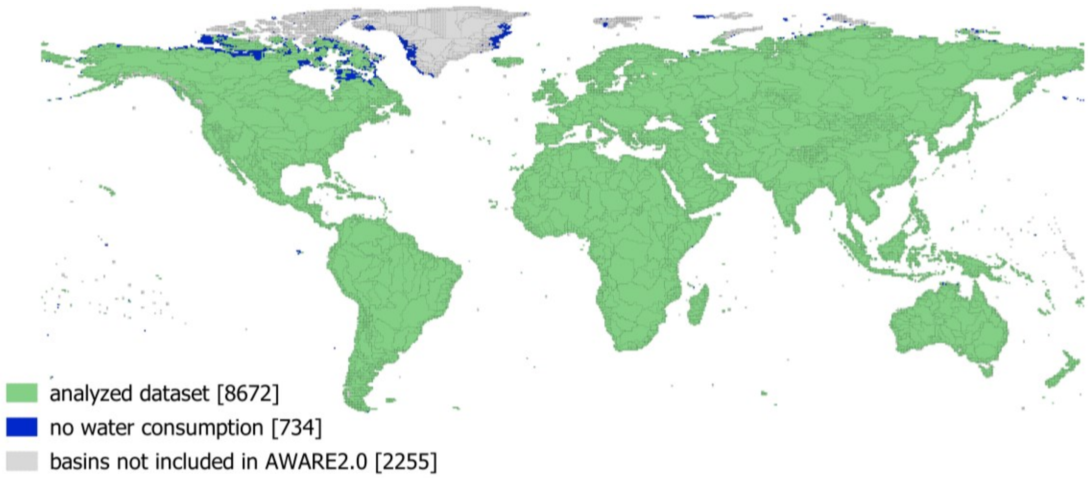

Figure S8: Basins remaining for the analysis of the AWARE2.0 dataset (modified from (Seitfudem 2022)).

S 2 Results Analysis

S 2.1 General results

Figure S9 shows the native-scale AWARE2.0 CFs. All other AWARE2.0 CFs (annual, country-level,…) are derived from these values. On a regional scale there is a clear seasonality, with CFs increasing in summer for most of Northern Africa and the Middle East, while the summer monsoon effects in Southeast Asia are clearly visible.

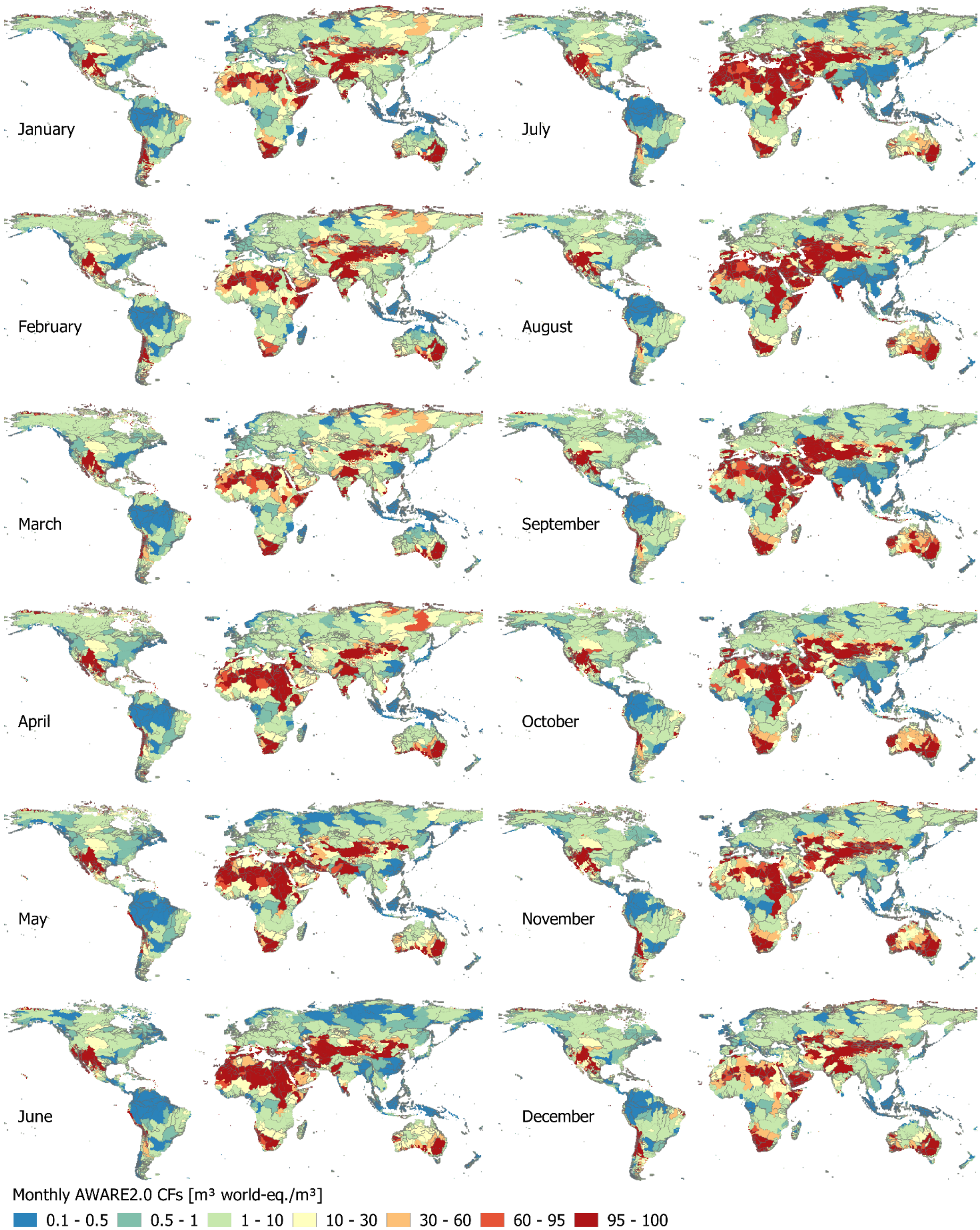

Figure S9: Monthly basin-level AWARE2.0 CFs.

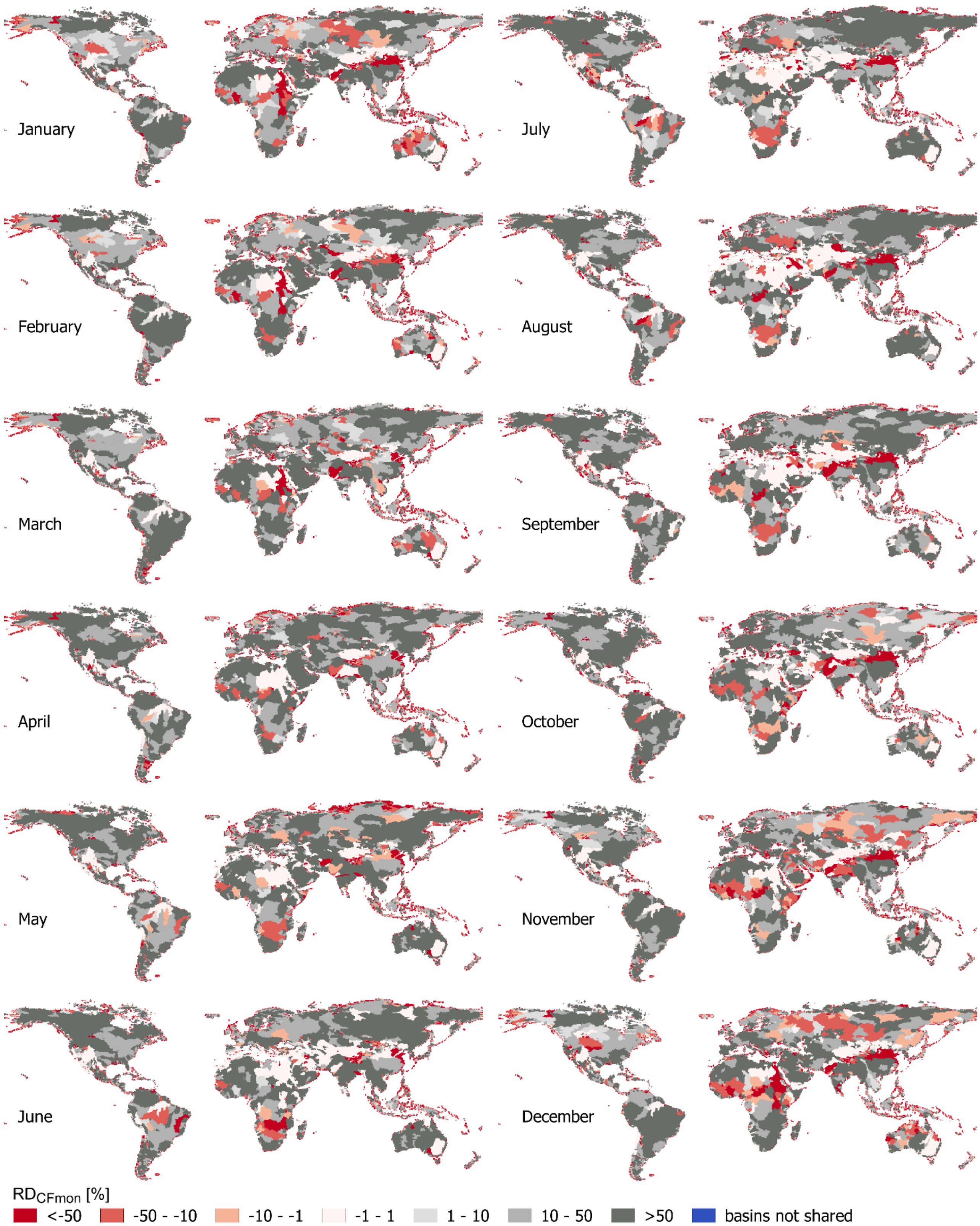

Figure S10: Spatial distribution of RD_{CFmon}. Red indicates AWARE2.0 CFs lower than in AWARE.

S 2.2 Comparison of AWARE2.0 to AWARE

The following figures show additional information on the datasets of AWARE and AWARE2.0. The correlation of the two datasets (Figure S11) is high (correlation coefficient for annual average CFs: 0.854) compared to a recent recalculation of annual AWARE CFs with an Integrated Assessment Model (Baustert et al., 2022, Supporting Information SUP1, correlation coefficient: 0.485).

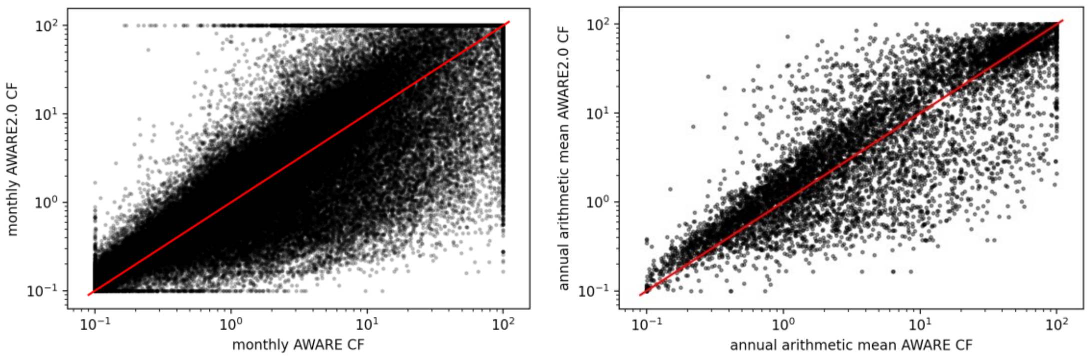

Figure S11: Change in CFs in the 8149 basins shared between AWARE and AWARE2.0. Red line to mark diagonal.

The recalculation of EFR coefficients corrected issues in the coefficients present in AWARE (Figure S12). The EFR coefficients on average change by 17%, which means that in less than 1% of basins the coefficients change at most by 10% all year round. In 3.7% of basins, the EFR coefficient at least once switches from “low flow” to “high flow” or the reverse (Figure S13). The correlation coefficient of the EFR coefficients is 0.612 (please note that they do not follow a normal or lognormal distribution).

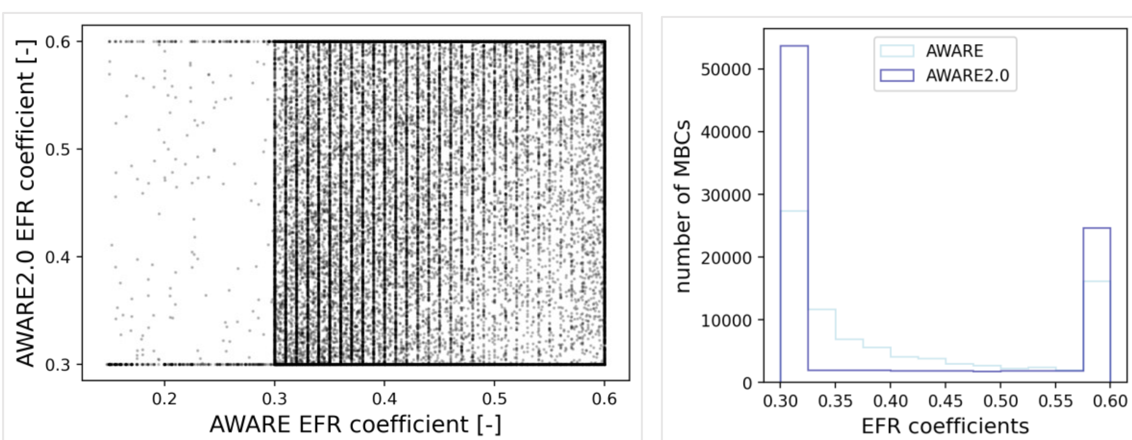

Figure S12: Structural differences between EFR coefficients of AWARE and AWARE2.0. Left: Scatter plot of EFR coefficients in AWARE and AWARE2.0. A small set of AWARE EFR coefficients (approx. 0.7%) are below the 0.3 threshold set by the Variable Monthly Flow method, probably due to a file handling error. In contrast to the coefficients of AWARE, the coefficients of AWARE2.0 are not rounded to two decimals. Right: Frequency distribution of EFR coefficients. Probably due to *averaging EFRs over a basin in AWARE, the share of intermediate flow regime EFRs is higher in AWARE than in AWARE2.0.*

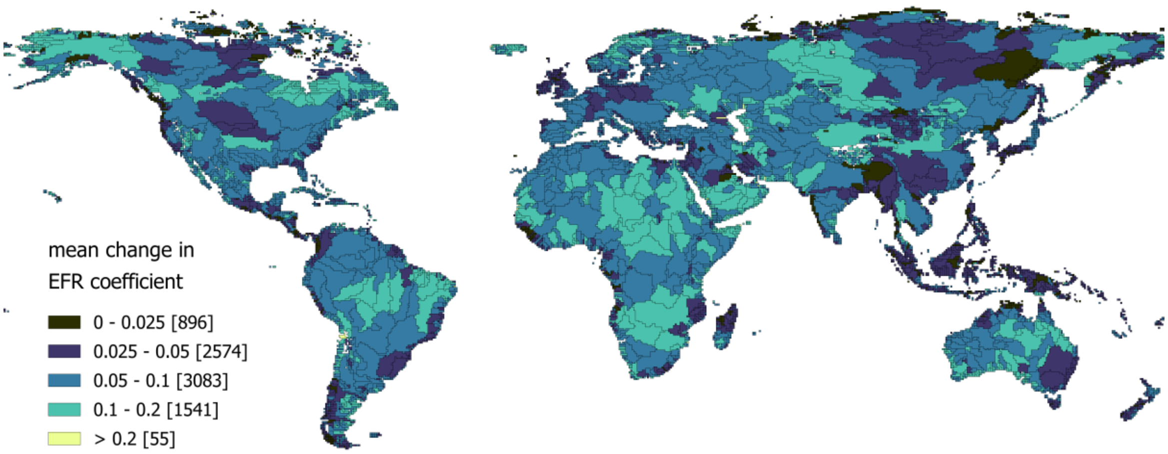

Figure S13: Annual mean of absolute changes in (monthly) EFR coefficients between AWARE and AWARE2.0.

S 2.3 Sensitivity analysis

The following is a detailed version of the sensitivity analysis done in the main article. First, there is a summary of the main findings provided for every variant. This is followed by the detailed analysis, including a brief introduction of the pursued question and additional methods used.

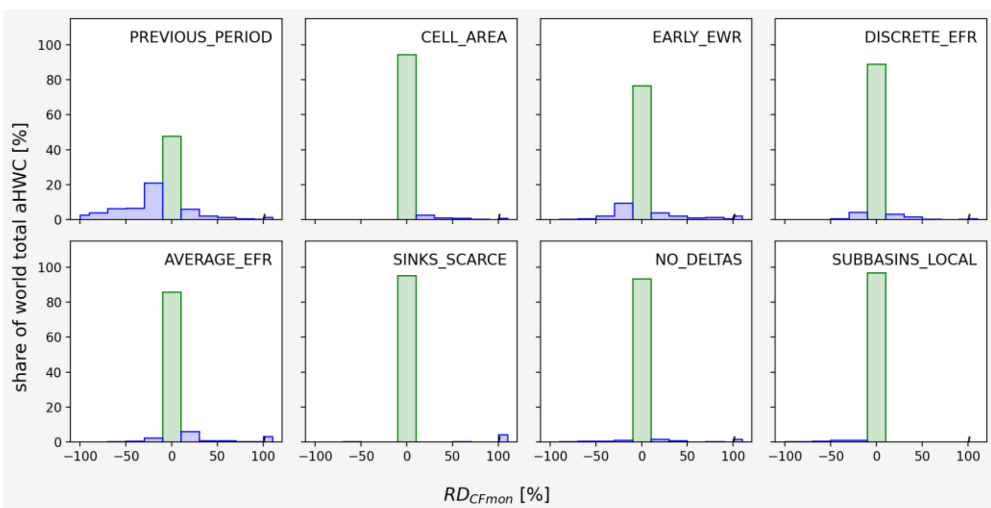

Figure S14: Share of HWC affected by different magnitudes of RD_{CFmon}. All RD_{CFmon} > 100% are summarized in the bin on the right-hand side.

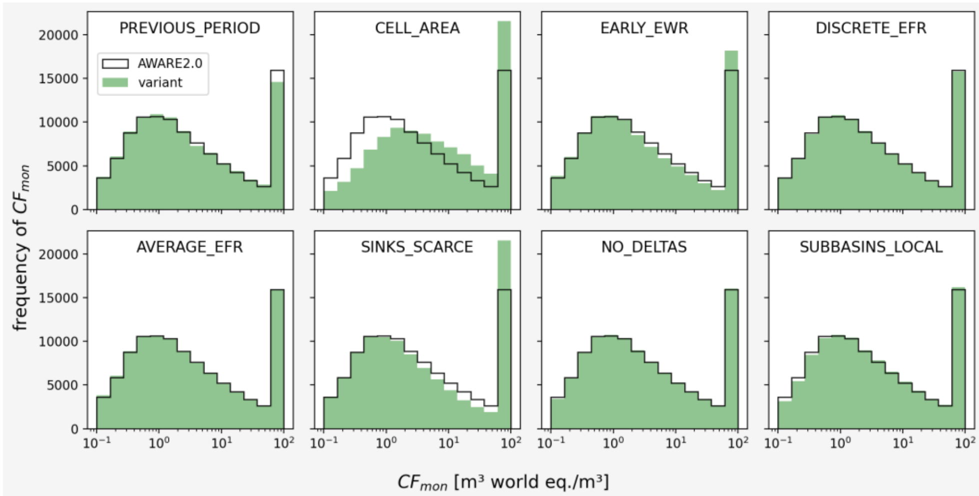

Figure S15: Frequency distribution of CF_{mon} for all variants. The distribution of monthly CFs in CELL_AREA is skewed towards higher CFs. In SINKS_SCARCE, the number basins where the CF equals 100 increased as well.

S 2.3.1 Summary of results

Please note that this summary uses information presented in the main article and new information presented in the following detailed sections. While the detailed sections and the article mostly treat the variants as deviation from AWARE2.0 ("variant y changes x% compared to AWARE2.0"), this summary aims to show the effect the improvements have on AWARE2.0.

Global variants

PREVIOUS_PERIOD

AWARE2.0 shows a higher global long-term *aHWC* total than PREVIOUS_PERIOD, with 42.8% of basins showing higher long-term *aHWC* every month. Long-term *aHWC* is predominantly linked to AMD reductions for AWARE2.0. However, an increase in long-term *aHWC* for a month or basin does not necessarily increase the CF, partly because of the cut-offs, partly because of the associated change in $AMD_{world\ avg}$. Of all variants, AWARE2.0 is most sensitive to this one (HWC_{RD10} >50%). With the switch to the temporal period of AWARE2.0, CFs increase for half of the human water consumption. 17% of CFs would increase if they were not outside the CF range, especially beyond the upper cut-off.

CELL_AREA

CELL_AREA shows the largest differences in CFs on a global scale, but the basins most affected are of low relevance. CFs are 6% higher in AWARE2.0 for basins for which grid cell and land area are almost identical (if not subject to cut-offs).

EARLY_EWR

A change in EWR can happen due to the absolute change in *NatAvail* as well as because of changes in the seasonal flow intensities. For most basins, the flow intensity (high, intermediate, or low flow) changes in less than 3 months. There is a slight trend to lower *NatAvail* for the EARLY_EWR period. Of the resulting EWRs, 54.4% are lower in EARLY_EWR than in AWARE2.0. The trends to higher or lower EWRs are of regional character and so is the resulting difference in CFs.

DISCRETE_EFR

DISCRETE_EFR shows only a small change in $AMD_{world\ avg}$. Most of the basins (91.6%) are at least once a year affected by the interpolation. With a HWC_{RD10} of 11.3%, the EFR coefficient interpolation is still relevant on monthly level. While the EFR cannot change more than ±33%, MBCs exist where the AMD changes by three orders of magnitude. CFs in the medium to high range tend to be affected stronger by the interpolation than CFs in the lower range.

AVERAGE_EFR

AVERAGE_EFR only affects one third of the basins directly via changed EFRs, from once a year up to every month. This means that for most of the basins the annual ranking does not change much and the RCC_{an} is the highest of all variants. However, the HWC_{RD10} equals 13.4%, which means that using the outflow cell EFR coefficient instead of averaging over the entire basin is one of the more LCA-relevant adjustments in this AWARE update, at least when using monthly CFs.

Local variants

SINKS_SCARCE

There are 781 basins (8.0% of aHWC) directly affected. AWARE2.0 shows a considerable decrease in global weighted average CFs (-9%) over SINKS_SCARCE. For basins other than inland sinks or their upstream subbasins, CFs increase 0.5% in AWARE2.0, because of more water being available on a global level. CFs of inland sinks are comparatively higher than CFs of other MBCs. However, there are basins where the CF is low, e.g., in the Kenyan Rift Valley.

NO_DELTA

For the majority of side branches in deltas, AWARE2.0 decreases the CF, while the CFs of the main branch increases. The side branch basins make up less than 3% of the global long-term water consumption, while the main branch basins make up 19%. However, the change in CFs is more pronounced for side branches than the main branches. With an HWC_{RD10} of 6.5%, the changes in NO_DELTA are rather unimportant compared to the other variants.

SUBBASINS_LOCAL

Each month on average 25% of the subbasins are directly affected by the new subbasin approach in AWARE2.0. Examples where the subdivision approach is used in most months are upstream subbasins of the Nile, Indus and Orange basin. Due to the subdivision approach in AWARE2.0, CF_{an} increases more than 50% in some subbasins, especially for the Nile, Indus and Ganges. For the remaining basins, the CFs are reduced by 6.2% due to the change in $AMD_{world\ avg}$.

S 2.3.1 Details regarding PREVIOUS_PERIOD

Main questions:
1. How would CFs differ if they were calculated from the previous reference period (1960 – 2010) instead of 1990 – 2019?
2. Does the switch to a more recent reference period result in more water consumption (long-term average) and less water availability (long-term average), leading to higher CFs?
3. Which temporal dynamic (increase/decrease in water availability) is more relevant for the update to AWARE2.0?
Additional Methods (not in article):
ActAvail and long-term actual human water consumption ($aHWC_{lt}$) are investigated. $RD_{ActAvail}$ and $RD_{aHWC,lt}$ describe the percentage change in these two variables on monthly level. To test whether a change in water consumption due to the new temporal reference period is closely linked to a change in CF, the ratios of long-term aHWC and CF are visually set into relation using a scatter plot.

PREVIOUS_PERIOD shows a higher total *ActAvail* and a lower total long-term *aHWC*. For 42.8% of the basins, PREVIOUS_PERIOD $aHWC_{lt}$ is lower in every month of the year (Figure S16). However, there are as well regions with higher $aHWC_{lt}$ for every month, mostly found in Scandinavia, Central and Eastern Europe, Northern Siberia, Central Africa, and Japan.

The $RD_{ActAvail}$ does not show such an obvious trend. For little more than half of the MBCs (50.5%) $RD_{ActAvail}$ is positive. Basins where $RD_{ActAvail}$ is positive every month represent 7.4% of all basins, while the basins where $RD_{ActAvail}$ never is positive represent 11.8%. Weighting by $aHWC_{lt}$ shows the relevance of the patterns for LCA (Table S3). Two thirds of $aHWC_{lt}$ are linked to MBCs where *ActAvail* is higher in PREVIOUS_PERIOD than in AWARE2.0 (Figure S17), thus two thirds of $aHWC_{lt}$ are linked to AMDs with the same dynamics. The majority of water consumption being linked to higher water availability in PREVIOUS_PERIOD indicates that the updated reference period in AWARE2.0 leads to decreased water availability for a relevant part of the globe.

In PREVIOUS_PERIOD, the frequency distribution of CFs is more centered with a lower number of CFs at the upper cut-off (Figure S15) and a reduction of global median and consumption-weighted average CFs.
The share of AWARE2.0 *aHWC* linked to changes in CFs is higher than for all other variants (HWC_{RD10} equals 52.2%). While 49% of the monthly CFs are higher in AWARE2.0, 40% are lower. The remaining 11% are outside the CF range limited by the cut-offs and represent 25% of $aHWC_{lt}$.
The CF cut-offs mask AMD changes, especially AMDs increasing in PREVIOUS_PERIOD (17% of $aHWC_{lt}$). This masking is one reason for CFs not

necessarily increasing along with $aHWC_{lt}$ increases in AWARE2.0 (see horizontal point cloud line in Figure S18). The discrepancy between $aHWC_{lt}$ and CFs dynamics is, amongst other regions, observable for China (Figure S19 vs. Figure S16).

Table S3: PREVIOUS_PERIOD: Share of global aHWC$_{lt}$ linked to changing variables. The difference in percentage for AMDs and ActAvail results from the new basin subdivision approach applied in the AMD calculation.

Variable	Higher in PREVIOUS_PERIOD	Lower in PREVIOUS_PERIOD	constant
CF	21.2%	53.5%	25.3%
AMD	33.1%	66.1%	0.8%
ActAvail	33.5%	65.8%	0.7%

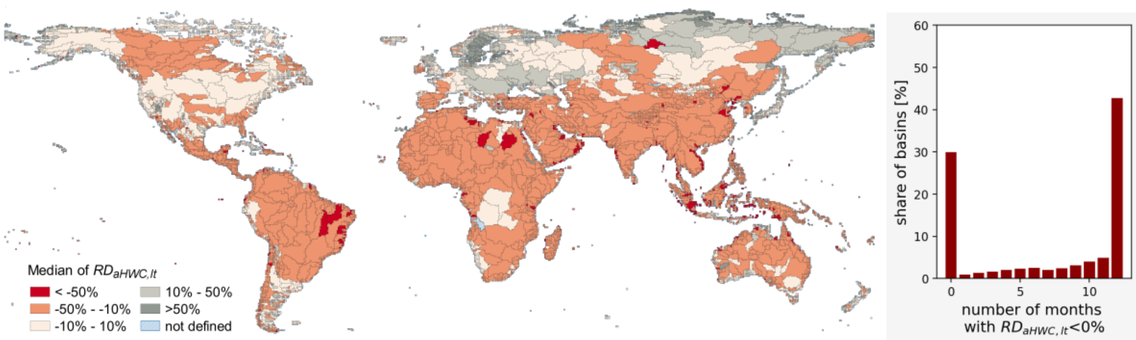

Figure S16: PREVIOUS_PERIOD: Spatial and temporal distribution of $RD_{aHWC,lt}$.

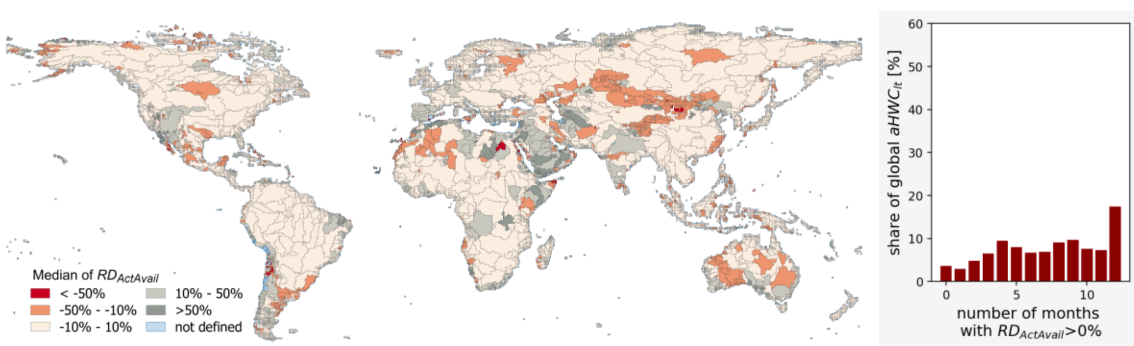

Figure S17: PREVIOUS_PERIOD: Spatial and temporal distribution of $RD_{ActAvail}$. Histogram distributes the basins according to their number of months with higher ActAvail in PREVIOUS_PERIOD (i.e. months where ActAvail reduced in AWARE2.0 due to new reference period). y-axis shows the share of global aHWC$_{lt}$ represented by these basins.

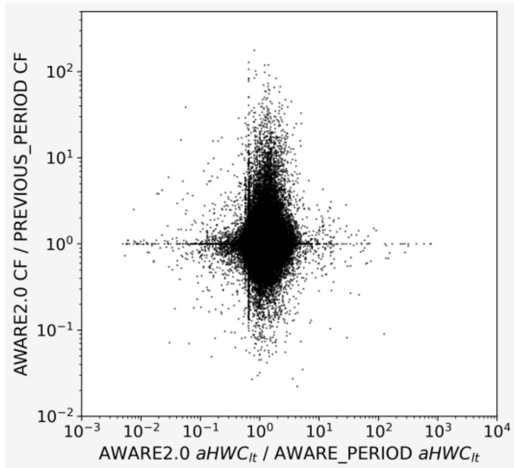

Figure S18: PREVIOUS_PERIOD: Relation between changes in long-term aHWC and CFs.

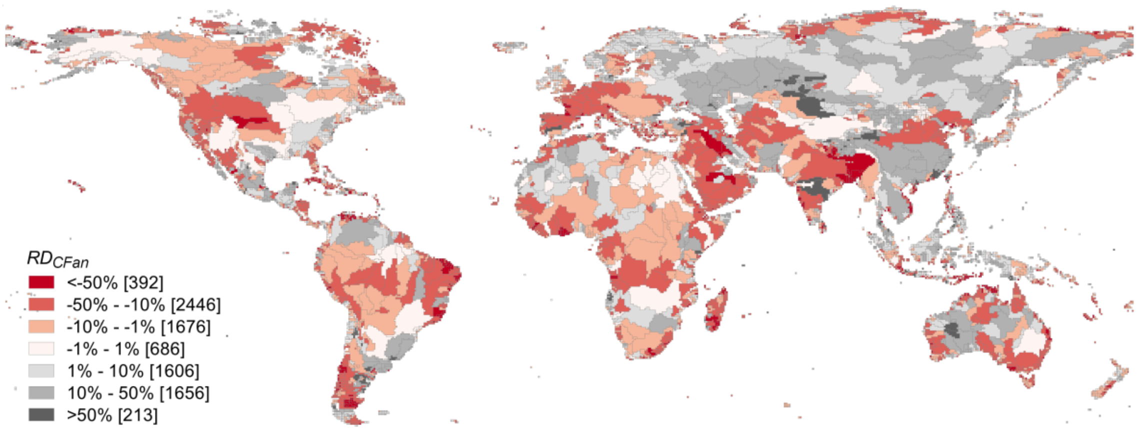

Figure S19: PREVIOUS_PERIOD: Change in annual arithmetic average CFs. Red indicates lower CFs in PREVIOUS_PERIOD (higher CFs in AWARE2.0).

S 2.3.1 Details regarding CELL_AREA

Main question: 1. How would CFs differ if they were calculated using the grid cell area instead of land area for AMD calculations?
Additional Methods (not in article): Because of the simple relationship between the modified calculation in CELL_AREA and the resulting CFs, only RD_{CFan} is investigated closer.

CELL_AREA has the lowest RCC_{an} of all variants, which indicates that in this variant the classification of basins as more water scarce or more water abundant is differing the most from AWARE2.0. CELL_AREA shows the largest change in median CF, but the weighted CF average reduces by less than 0.1% and HWC_{RD10} equals only 5.2%, indicating that mostly small watersheds are directly affected. One third more CFs are cut-off at 100 m³ world-eq./m³ and 42% less at 0.1m³ world-eq./m³ (compare Figure S15).

While the basins affected the most are on the coast and small islands, some inland basins are indirectly affected because of the delta aggregation and basin subdivision approach (Figure S20). Further information regarding the difference between grid cell and land area and its influence on original AWARE can be found in (Baustert et al. 2022; Seitfudem 2022).

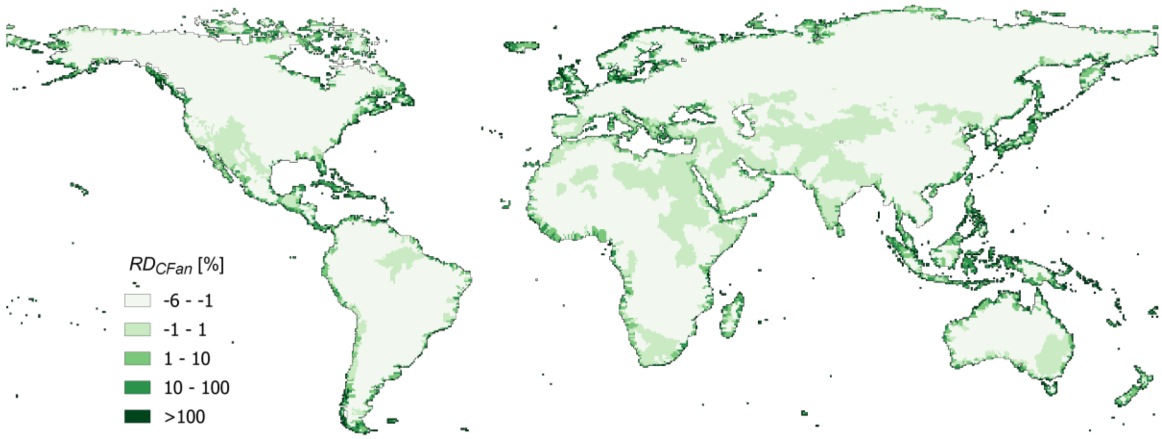

Figure S20: CELL_AREA: RD_{CFan} for AWARE2.0 vs. CELL_AREA. For basins and subbasins where the CF change dominantly results from the reduced AMD_{world_avg}, the RD_{CFan} is around -6%. Values close to 0% appear for basins with many monthly CFs at cut-offs.

S 2.3.1 Details regarding EARLY_EWR

Main questions:
1. How would the CFs differ if AWARE2.0 was calculated with EWR values retrieved from the first half of the 20th century to reduce the influence of anthropogenic climate change?
2. How does this difference relate to changes in NatAvail, flow intensity and the EWR?
Additional Methods:
To study the change in NatAvail in EARLY_EWR, the numbers of months affected by increased or decreased NatAvail was determined using $RD_{NatAvail}$. Whether there was a change in EFR coefficients was determined by counting the number of months in which the EFR changes its flow regime (low, intermediate, high flow). Additionally, RD_{CFan} and RD_{EWR} (relative difference of monthly EWRs) were used to evaluate the changes in CF.

EARLY_EWR shows a considerably higher number of CFs at the cutoff of 100 (+17.7%) and accordingly a slight upwards shift in CF weighted average. Of all variants, it has the second highest HWC_{RD10}. There is a spatial focus regarding strong changes in annual CFs (Figure S24): EARLY_EWR CFs are higher in Western Africa, the Middle East, the Tibetan Plateau, and regions towards the South and Nort pole in the Americas, but lower in Australia, Europe, and Russia.

A change in EWR considering the variant EARLY_EWR can result from an absolute change in *NatAvail* as well as from changes in the monthly flow pattern. In 42.4% (52.7%) of basins, RD_{NatDis} is positive (negative) in the majority of months, which means that there is a slight trend to *NatAvail* being lower in EARLY_EWR than AWARE2.0 (Figure S21). Basins where *NatAvail* in EARLY_EWR is higher for 11 or all 12 months are mostly found in Africa, the Middle East, East Asia, Northern and South America.

The number of MBCs categorized as either of high, intermediate, or low flow intensity differs less than 1% between AWARE2.0 and EARLY_EWR. For more than 80% of basins (90.7% of AWARE2.0 long-term aHWC), the category changed in less than 3 months (see Figure S25). For a subset of basins representing 0.2% of the global HWC total, they change in more than 6 months.

The multiplication of EFR coefficient and *NatAvail* result in the EWR. Since the EWR is closely linked to both variables, in most cases it just changes proportionately to the *NatAvail* (Figure S23). In line with the finding that *NatAvail* rather reduces in EARLY_EWR, the RD_{EWR} is negative for 54.4% of the MBCs, which means that the EWRs in EARLY_EWR are rather lower compared to AWARE2.0. For EARLY_EWR, the annual median of EWR increases >10% towards the poles in the Americas, in most of Africa, the Middle East, East Asia (Figure S22). Decreases >10% in the annual median are, for example, found in Australia, Europe and Scandinavia, Russia, the US, and Canada.

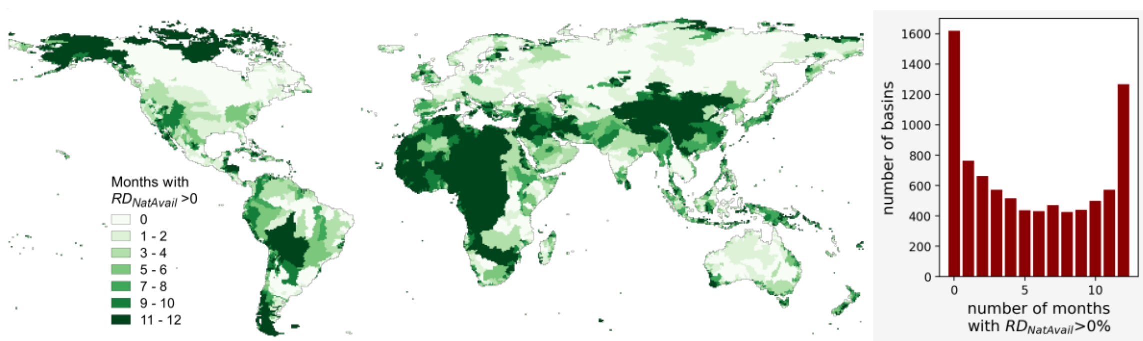

Figure S21: EARLY_EWR: Number of months with increase or decrease in NatAvail used for the EWR, EARLY_EWR compared to AWARE2.0.

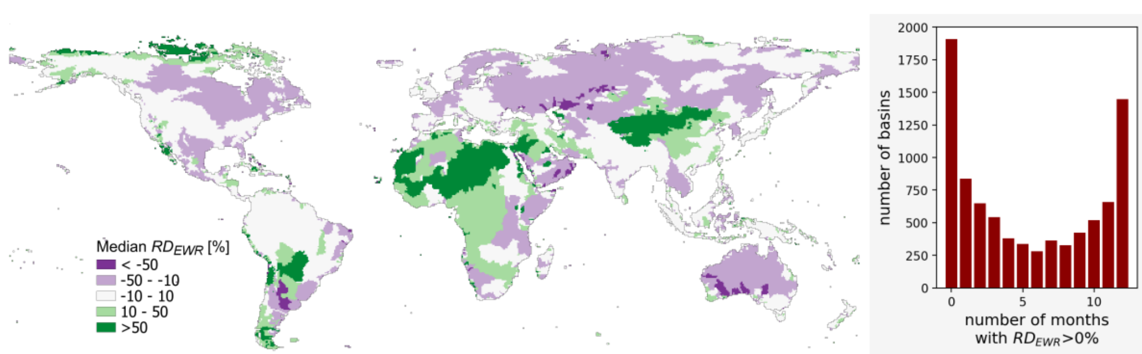

Figure S22: EARLY_EWR: Median change in EWRs, EARLY_EWR compared to AWARE2.0.

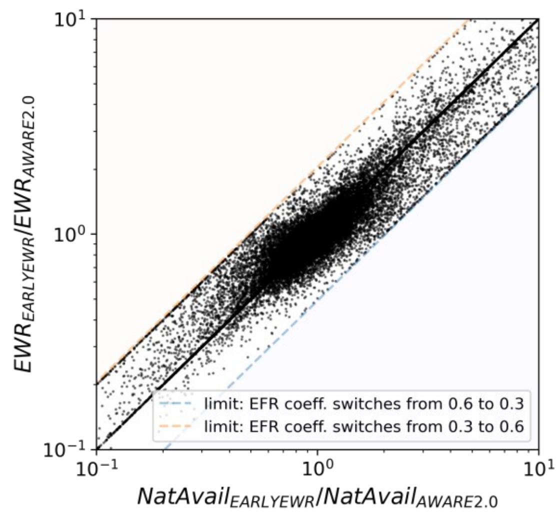

Figure S23: EARLY_EWR: Relationship of changes in NatAvail to changes in EWR (detail). In most of the MBCs, EWR changes directly proportional to NatAvail. However, if the EFR coefficients do not remain constant, the change can be to up to double the change in NatAvail (NatAvail increases by 5%, EWR increases by 10%, orange line) or up to half the change in NatAvail (blue line).

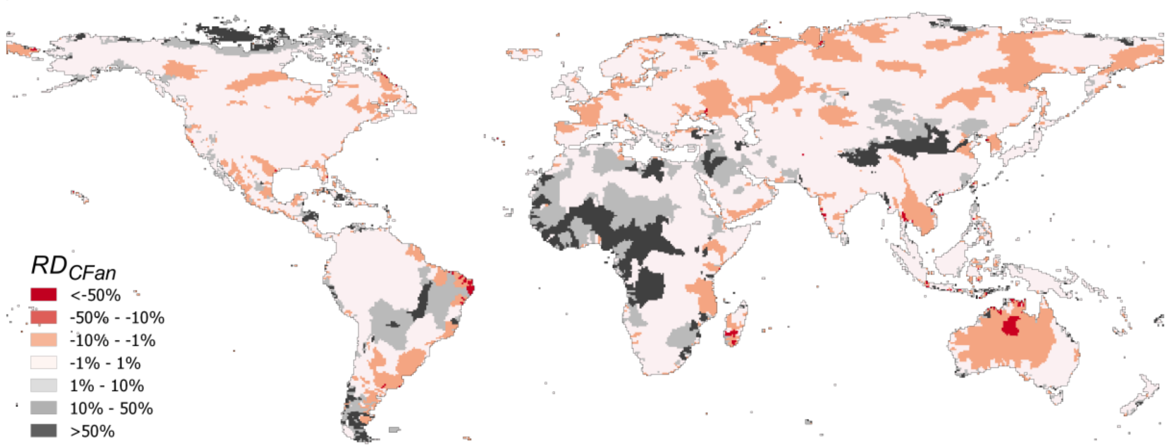

Figure S24: EARLY_EWR: Change in annual arithmetic average CFs, EARLY_EWR compared to AWARE2.0.

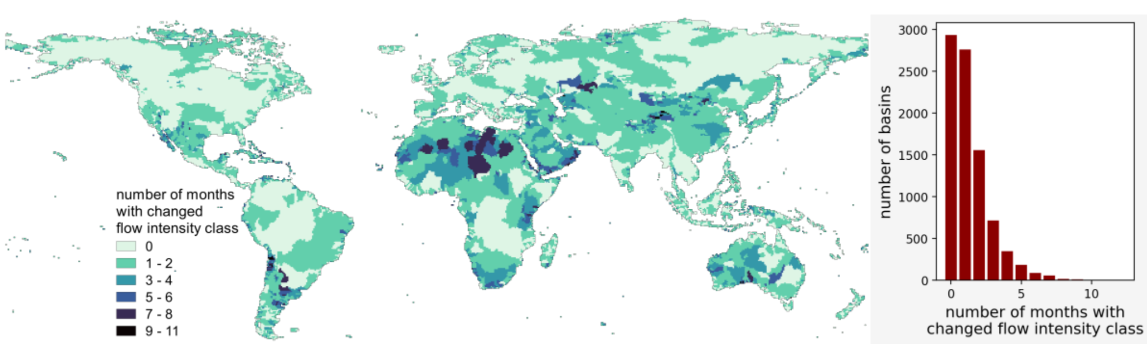

Figure S25: EARLY_EWR: Number of basins with changed flow intensity (high, intermediate or low) between AWARE2.0 and EARLY_EWR.

S 2.3.2 Details regarding DISCRETE_EFR

Main questions:
1. How many basins are affected by the interpolation and how does this affect the CFs?
2. For MBCs which strongly change their EFR coefficient, does this lead to a different CF?
3. Are CFs of different orders of magnitude differently affected?

Additional Methods:
The relevance of the interpolation to MBCs with flow conditions close to the limits of the "intermediate" bin was tested separately. The term MBC_{step} is used to identify MBCs with intermediate flow intensity close to the boundaries 0.4 and 0.8. "Close" here means a flow intensity between 0.4 and 0.41 or 0.79 and 0.8. The change in CF for these MBC_{step} is then assessed in relation to the order of magnitude of the CFs.

DISCRETE_EFR shows a relatively high RCC_{an} (0.999) and a comparatively small change in $AMD_{world\ avg}$. 91.6% of all basins record a change in EFR coefficient (Figure S26). There are 1246 MBC_{step}, representing 1.2% of all MBCs. There is no spatial pattern visible regarding the number of months affected. While the maximum number of months affected is nine, the most common number is two.

The change in EWRs due to the interpolation is limited to maximum ±33%. However, there are individual basins and months with extreme ratios between their AMDs in AWARE2.0 and in DISCRETE_EFR (Figure S27) and 15% of all MBCs show a change in AMD by more than 10% (after application of the subdivision mechanism for large river basins).

In general, the magnitude of changes in CFs due to the implementation of the EFR coefficient interpolation is positively correlated with the change in EFR coefficients (Figure S28, left). Relative changes in CFs due to the interpolation are larger for intermediate and high CFs than for low CFs (Figure S28, right). For 6% of the basins, RD_{CFan} exceeds the ±10% margin (Figure S29), however the HWC_{RD10} equals 11.3%. This positions the influence of the EFR coefficient interpolation on AWARE2.0 in the middle range between the other improvements.

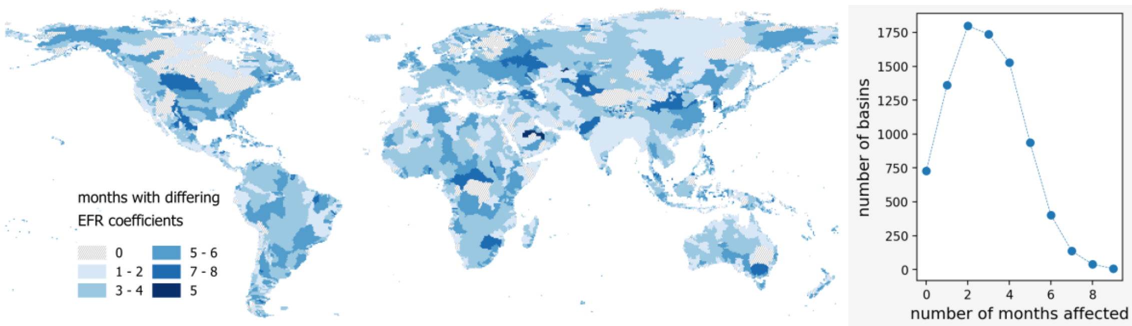

Figure S26: DISCRETE_EFR: Number of months with differing EFRs for intermediate flow regimes, AWARE2.0 compared with DISCRETE_EFR

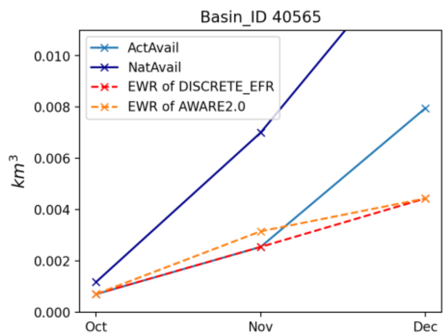

Figure S27: DISCRETE_EFR: Reason for a ratio of 4250.4 between AMDs in November, Basin_ID 40565: While in AWARE2.0 the EWR is 24% higher than ActAvail, in DISCRETE_EFR it is 0.006% higher. The ratio between both percentages determines the ratio of the AMDs.

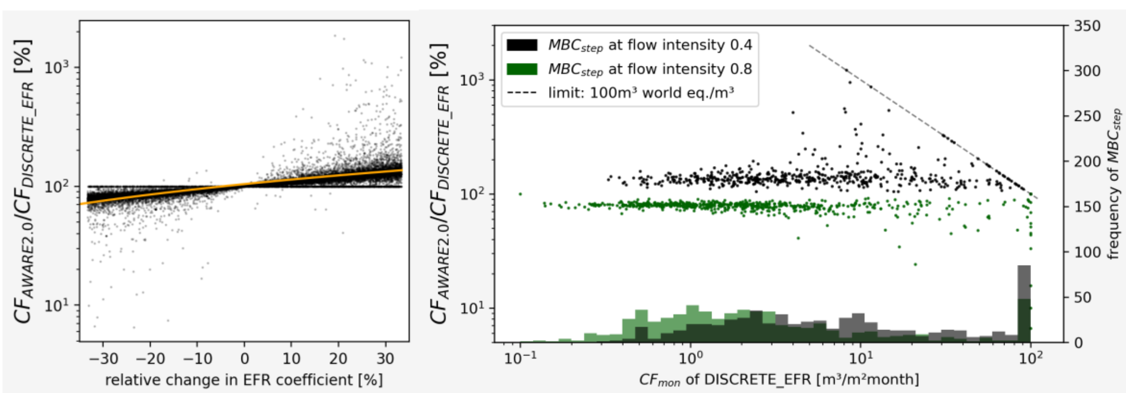

Figure S28: DISCRETE_EFR: Changes in CFs due to changes in EFR. Left: Ratio of monthly CFs between AWARE2.0 and DISCRETE_EFR, in relation to relative change in EFR coefficients due to interpolation. The orange line indicates a trend based on a linear least-squares regression. There are 24717 values in the plot of which 8.4% show no change in CF because they are either at the cutoff of 100 (98%) or 0.1 (2%). Right: The same ratio in relation to the DISCRETE_EFR CFs for MBC_{step} only. The higher the CF in DISCRETE_EFR, the larger the relative changes due to the EFR coefficient interpolation.

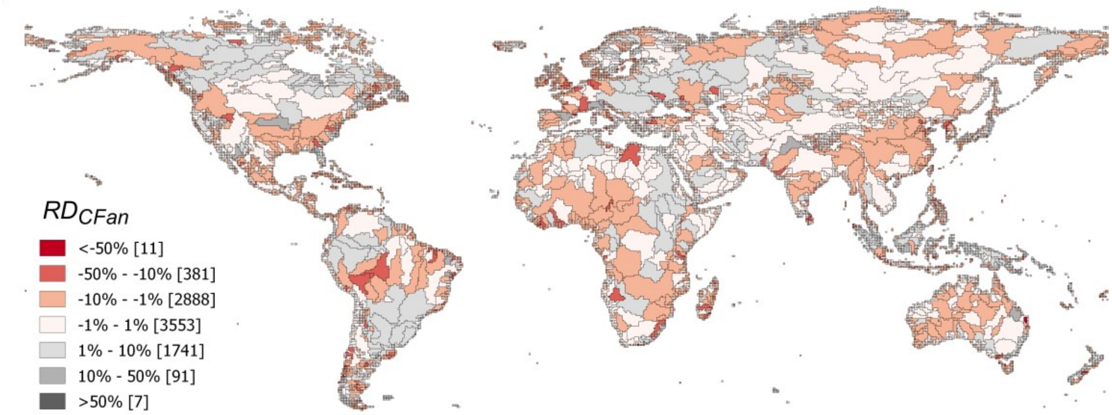

Figure S29: DISCRETE_EFR: Relative Difference in annual arithmetic CF average between AWARE2.0 and DISCRETE_EFR.

S 2.3.1 Details regarding AVERAGE_EFR

<u>Main questions:</u>
1. How much are the CFs impacted by not averaging the EFR coefficients over a basin?
2. How many basins are affected by a change in EFR coefficient?
<u>Additional Methods:</u>
For AVERAGE_EFR, RD_{CFan} was evaluated and it was investigated how many EFRs change more than ± 0.01% between AWARE2.0 and AVERAGE_EFR.

AVERAGE_EFR is the variant most similar to AWARE2.0. The RCC_{an} is the highest of all variants. However, still 13.4% of water consumption show CF changes larger ±10%. These changes are restricted to 13.8% of the basins (Figure S31). It is important to note that a changed EFR is only possible in basins larger than one grid cell, which reduces the number of potentially affected basins automatically by 59.4%. Since in 68.6% of basins the monthly EFR coefficients does not change (setting threshold at ±0.01% change, Figure S32), in most of the basins where a changed EFR coefficient is theoretically possible, a change happens at least once a year, although it might be small.

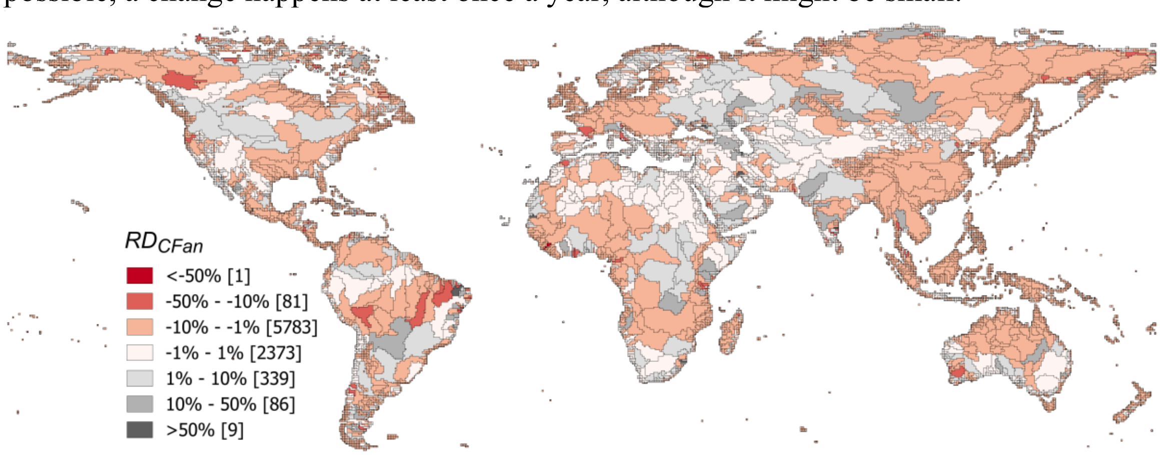

Figure S30: AVERAGE_EFR: Change in annual CFs, AVERAGE_EFR compared to AWARE2.0.

Figure S31: AVERAGE_EFR: Basins where relative change in CFs exceeds ±10% at least once a year.

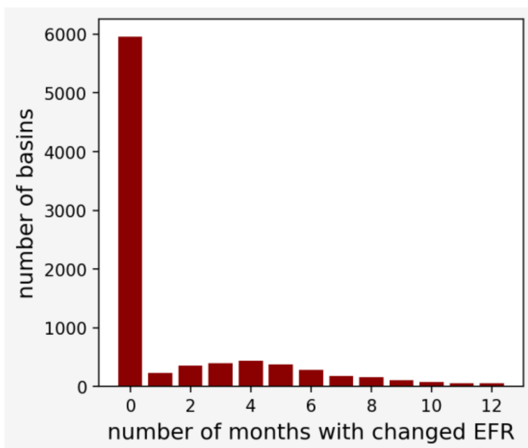

Figure S32: AVERAGE_EFR: Number of basins and months where the EFR coefficient changes more than ± 0.01% between AVERAGE_EFR and AWARE2.0.

S 2.3.2 Details regarding SINKS_SCARCE

Main questions:
1. Does the approximation approach for inland sinks lead to unrealistically low CFs or are they still rather high (as suggested by the property of being inland sinks)?
2. How are the CFs in general affected by using the approach for inland sinks?
Additional Methods:
None

781 basins are inland sinks (8.0% of aHWC), which means that they are directly influenced by the approximation for water availability (*ActAvail* and *NatAvail*) (Figure S33). In addition, 7 basins are affected because they are upstream to an inland sink basin. The remaining basins can indirectly be affected by a change in AMD_{world_avg}, as long as

they are not cut-off. Since the AMD_{world_avg} is 0.4% lower in SINKS_SCARCE than in AWARE2.0, this means that they reduce by 0.4%.

Although the CFs of most basins are reduced slightly, SINKS_SCARCE shows a considerable increase in global weighted average CFs (+9%). This is because the inland sinks with their value of 100 m³ world-eq./m³ shift the weighted average upwards.

In AWARE2.0, CFs of inland sinks are comparatively higher than CFs of other MBCs (Figure S34). Even with the approximation of *ActAvail* and *NatAvail* as done for AWARE2.0, 34% of the affected MBCs remain at 100 m³ world-eq./m³. However, there are basins where CF <1 m³ world-eq./m³, e.g., in the Kenyan Rift Valley or around Lake Chad.

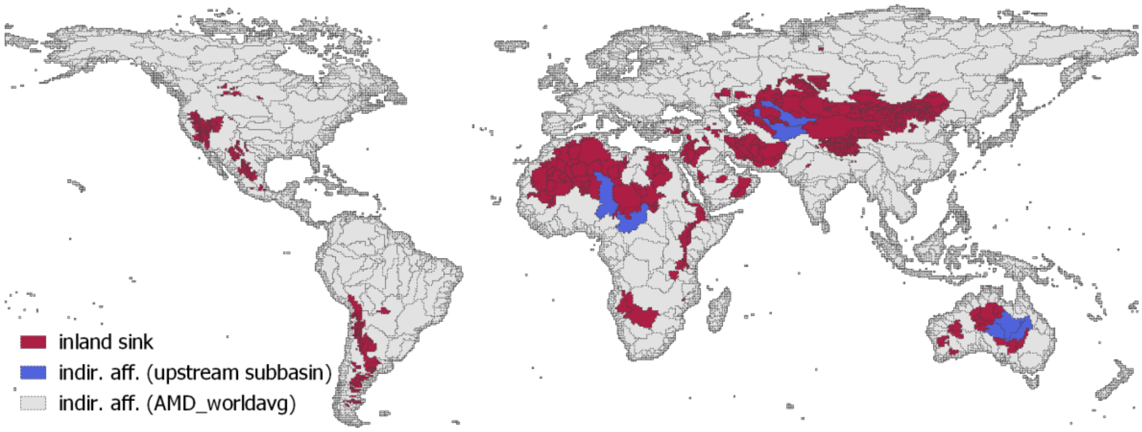

Figure S33: SINKS_SCARCE: Basins affected by approximations for inland sinks.

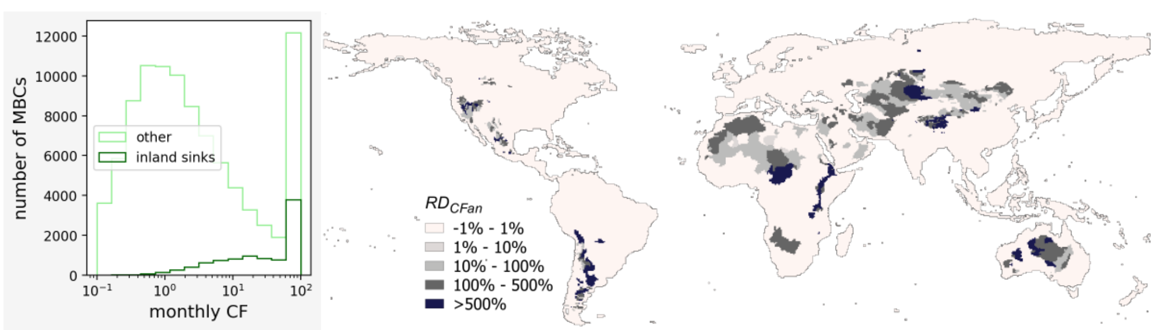

Figure S34: SINKS_SCARCE: Left: Frequency distribution of monthly CFs in AWARE2.0 using the approximation approach for inland sinks, separating them from the other basins. Right: RD_{CFan} for SINKS_SCARCE. Dark blue shows that the inland sink approximation in AWARE2.0 results in an annual arithmetic average CF of less than 16 m³ world-eq./m³.

S 2.3.3 Details regarding NO_DELTA

<u>*Main questions:*</u>

1. Which basins are affected by the delta aggregation in AWARE2.0?

2. Does the delta aggregation lead to decreased CFs for side branches of deltas?

<u>Additional Methods:</u>
Here, main branch and side branches of a delta are distinguished, the main branch being the basin with the largest number of grid cells and the side branches being the basins not directly profiting from these upstream grid cells in WaterGAP2.2e.

Using the delta aggregation directly affects 22.1% of long-term aHWC (228 basins, Figure S36). Of these, the 50 main river basins, make up 19.3% of long-term aHWC.

NO_DELTA shows an increased maximum AMD compared to AWARE2.0, because high water availability in the Amazon delta is not anymore shared with side branches of the delta. The $AMD_{world\ avg}$ and arithmetic AMD average decrease in NO_DELTAS. In NO_DELTA, the majority (69.3%) of delta side branch CFs are higher, the same holds for annual CFs. Monthly CFs of main branch basins mostly decreased (59.0 %, see Figure S37).

Figure S35: NO_DELTA: RD_{CFan} for NO_DELTA. Note that for this figure a different color scheme was chosen than for the other RD_{CFan} maps.

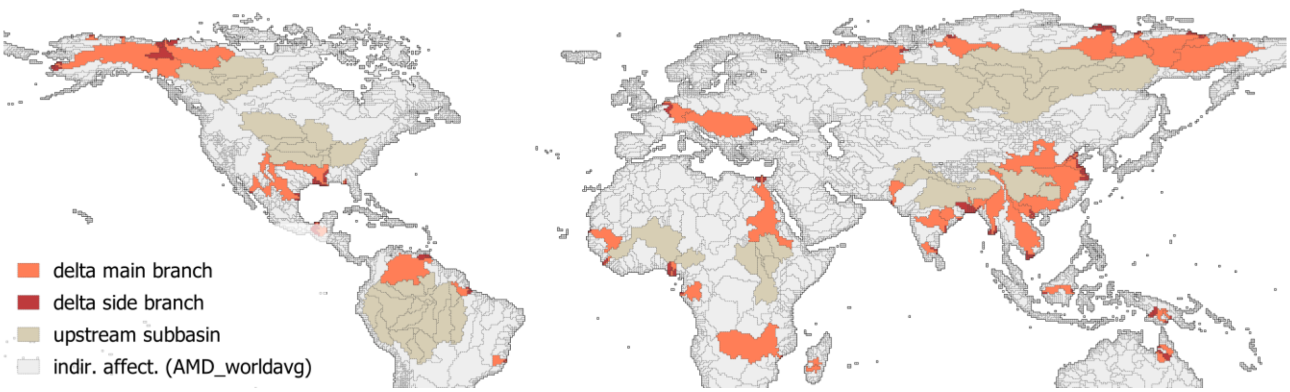

Figure S36: NO_DELTA: Basins affected by the delta aggregation in NO_DELTA.

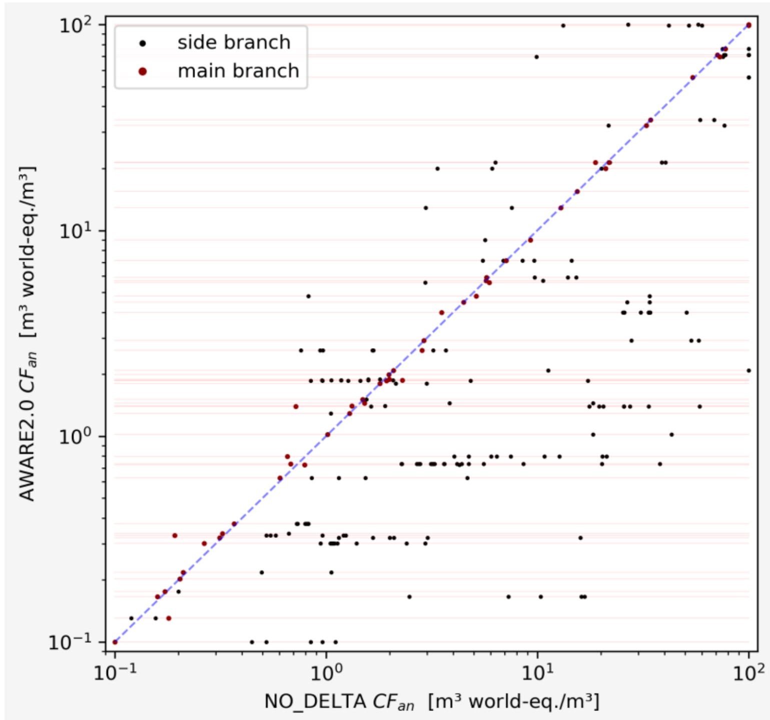

Figure S37: NO_DELTA: Annual arithmetic average CFs of basins affected by the delta aggregation. In AWARE2.0, all annual average CFs of the basins in a delta are the same, since the delta is treated as one basin. Most of the main branch CFs are close to the diagonal, indicating that they did not change much between AWARE2.0 and NO_DELTA. The side branch CFs in NO_DELTA often are higher than the main branch CF and also than their AWARE2.0 CF.

S 2.3.4 Details regarding SUBBASINS_LOCAL

Main questions:
1. How high is the share of subbasins actually impacted by the new approach, given that there is the exception for high local AMDs?
2. How much do the CFs change due to the new approach to subbasins?
Additional Methods:
CFs and AMDs of the subdivided basins are compared.

SUBBASINS_LOCAL shows a large increase for the maximum AMD over AWARE2.0 (+712%), as there is one subbasin in the Amazon basin (Basin_ID: 54900) which, seen as an isolated basin, has a disproportionately high water availability on a relatively small area. In all subdivided basins, the final AMDs of SUBBASINS_LOCAL are equal to or higher than the AMDs of AWARE2.0 (Figure S38). Therefore, for SUBBASINS_LOCAL the CF_{an} heavily decreases (more than 50%) in some of these subbasins, especially for the Nile, Indus and Ganges. Where local AMDs equal final AMDs, the CF increases by 6.6% because of the increase in $AMD_{world\ avg}$ (given the CF is not cut-off). Not including the side branches of large river deltas, all subbasins together represent 39.0% of the long-term $aHWC$. However, the HWC_{RD10} of SUBBASINS_LOCAL equals 3.3%, which is the lowest value of all variants. This is because the subbasins are not all affected equally by the methodological change: Each month, an average 75% of the 129 subbasins are not subject to the new subdivision approach but retain their initial AMD (Figure S39, monthly overview in Figure S40).

Examples where the subdivision approach is in effect in most months are upstream subbasins of the Nile, Indus and Orange basin. Consequently, in SUBBASINS_LOCAL, the impact of water consumption in these upstream subbasins is underestimated because it does not consider the water availability downstream.

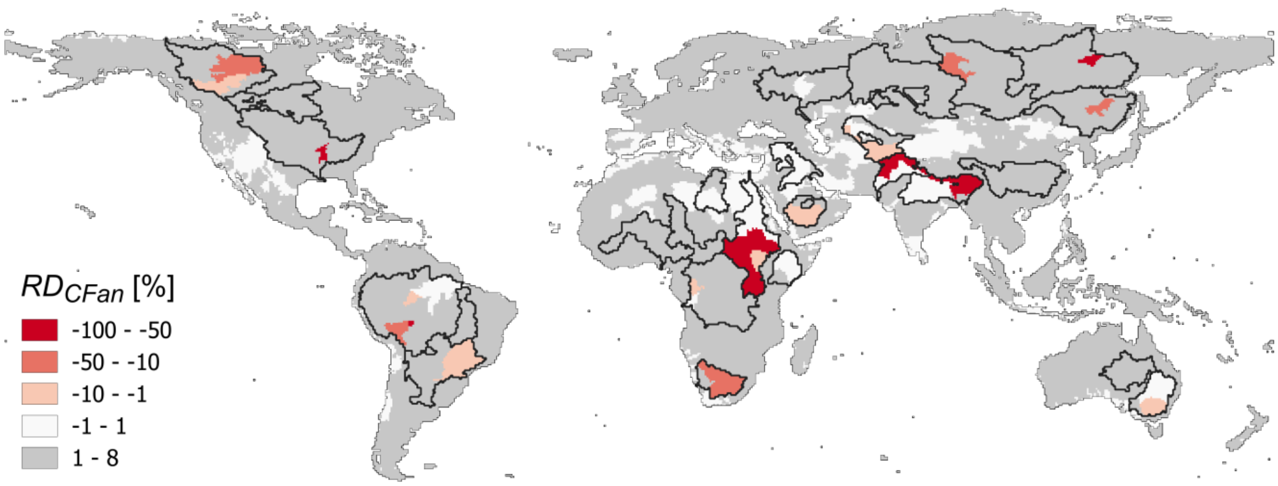

Figure S38: SUBBASINS_LOCAL: RD_{CFan} for SUBBASINS_LOCAL.

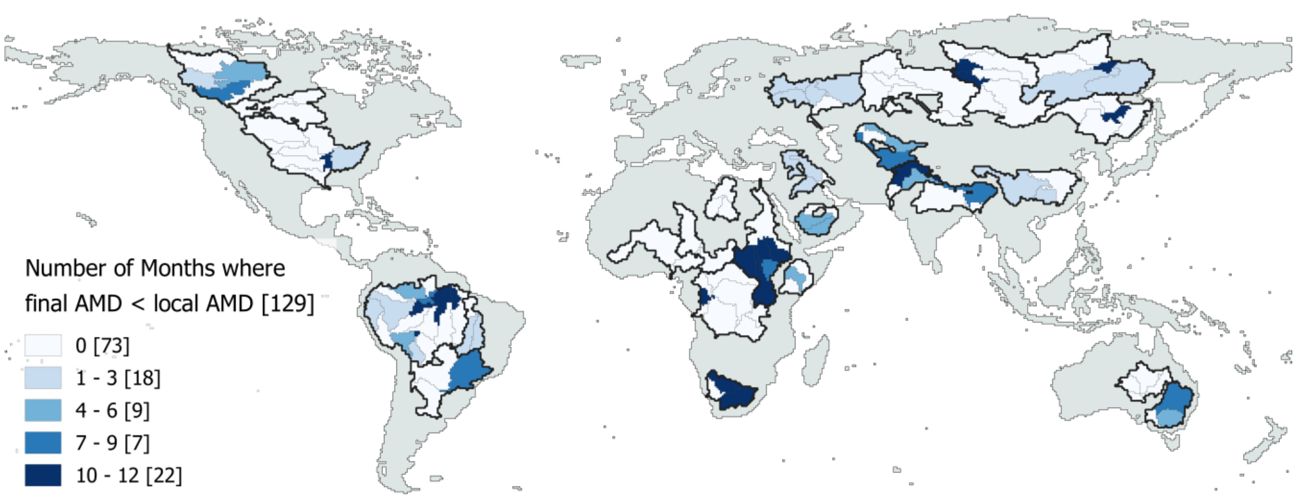

Figure S39: SUBBASINS_LOCAL: Number of months where AWARE2.0 subbasin approach comes into effect. This is always when the new approach resulted in an AMD lower than the local AMD.

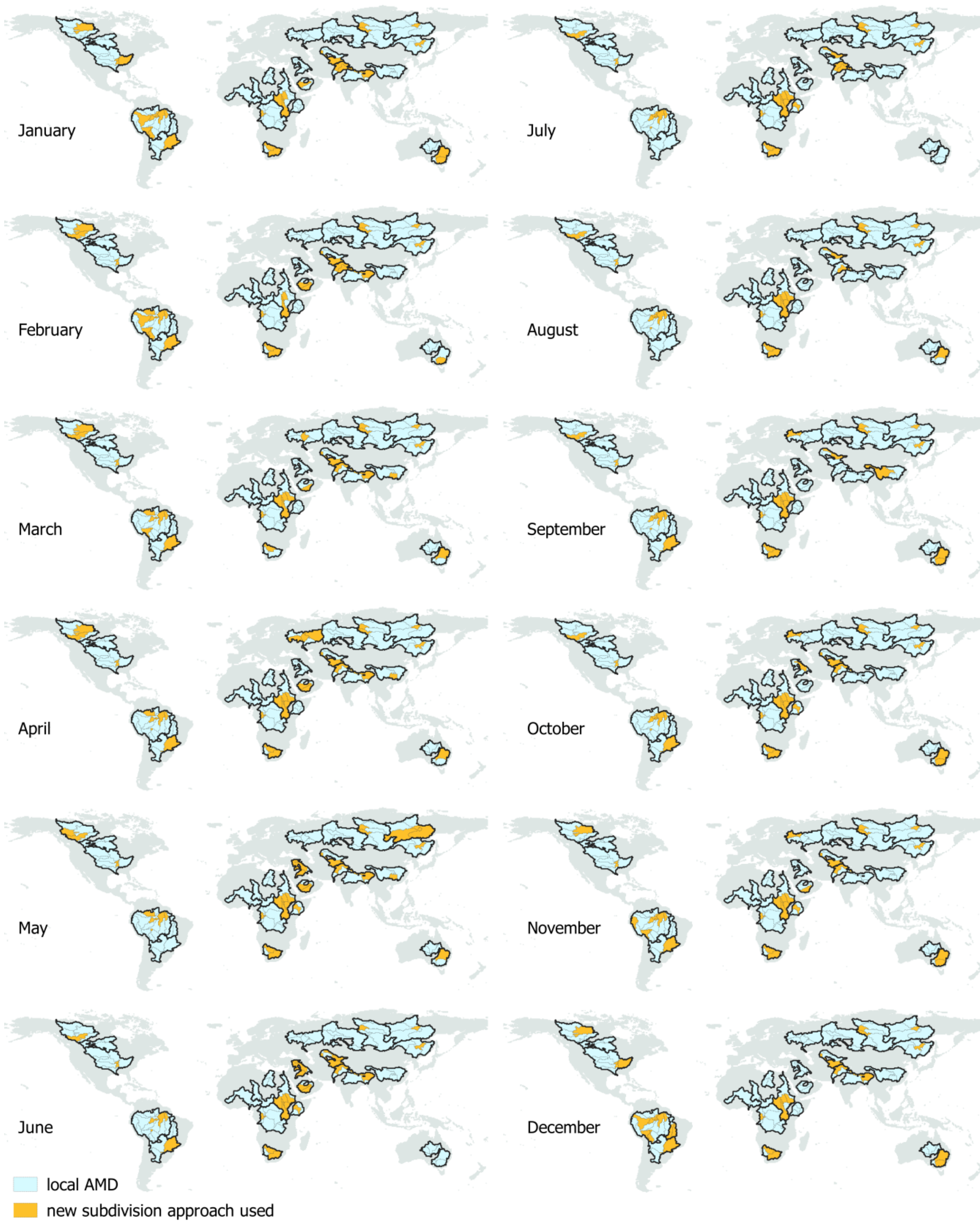

Figure S40: Relevance of the new method on the final CFs. Where the local AMD is used, the subdivision approach does not have a direct effect on the CF.

S 2.4 Relevance of WaterGAP2.2e model output

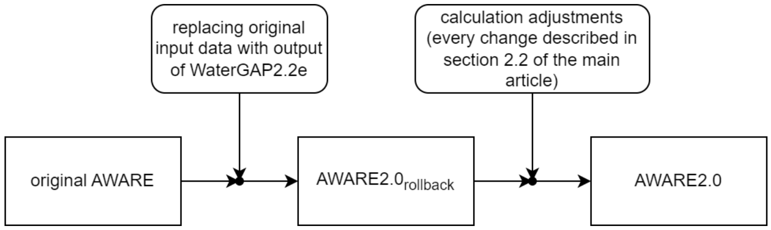

Figure S41 Relation between AWARE, AWARE2.0$_{rollback}$ and AWARE2.0.

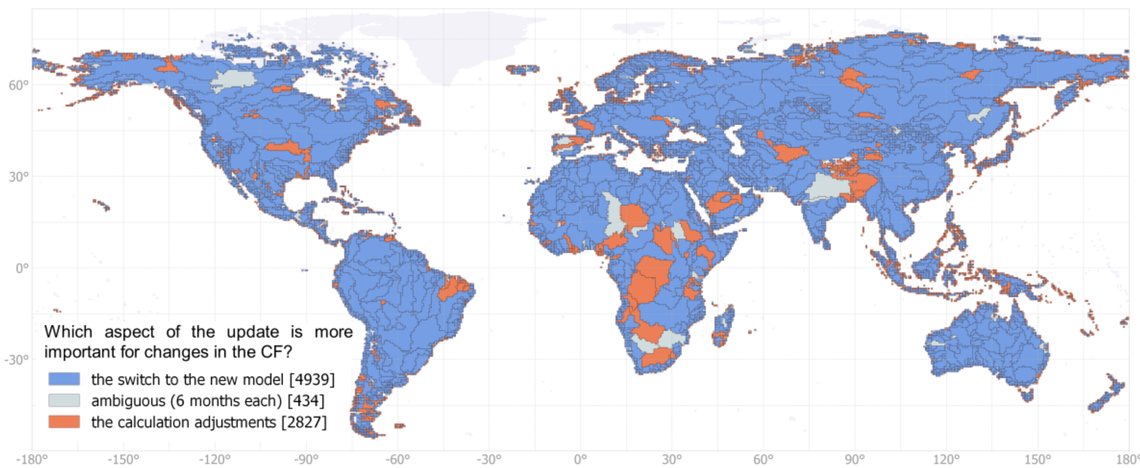

Figure S42: Relevance of switching from the original input data of AWARE to WaterGAP2.2e, compared to subsequently adjusting the calculations for AWARE2.0. Relevance is indicated by the number of months in which aDTM$_{CFmon,model}$ or aDTM$_{CFmon,adjustments}$ are higher. Note that due to the way the CFs are calculated, the change in AMD$_{world\ average}$ and the cut-offs can be decisive for this metric. For a comparison by AMD, see Figure S43.

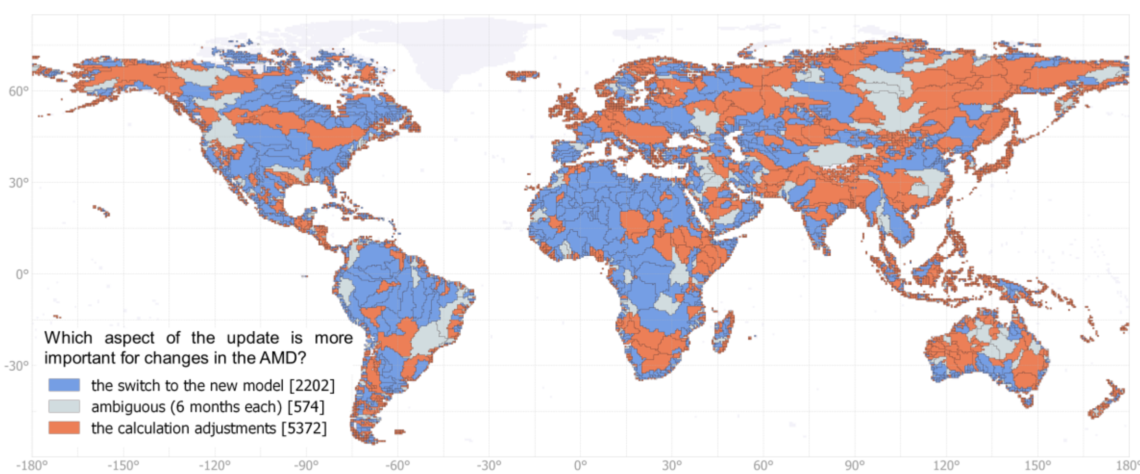

Figure S43: Relevance of switching from the original input data of AWARE to WaterGAP2.2e, compared to subsequently adjusting the calculations for AWARE2.0. Relevance is indicated by the number of months in which the difference in AMDs between AWARE and AWARE2.0$_{rollback}$ exceeds or falls below the difference between AWARE2.0$_{rollback}$ and AWARE2.0.

S 2.5 Case study Yellow River

The Yellow River watershed is one of the most water consumption intensive watersheds of China. In AWARE2.0, the annual arithmetic average CF (CF_{an}) of the Yellow River watershed is signficantly lower than in AWARE: 72.7 m³ world-eq./m³ in AWARE vs. 20.0. m³ world-eq./m³ in AWARE2.0. For annual weighted averages, this difference persists. In general, absolute changes between AWARE and AWARE2.0 are less relevant for LCA application than changes in the overall ranking of basins. However, the following paragraphs investigate the changes in the Yellow River basin since they are strong and also considerably influence the change in the country aggregation for China (see section S 2.5.1).

Changes in the $AMD_{world\ average}$ cannot explain the change, since the $AMD_{world\ average}$ increases from AWARE to AWARE2.0. The change rather is in the monthly pattern of CFs (Figure S44). While in AWARE the CFs are at the upper cut-off from June to January and decrease in spring, the CFs in AWARE2.0 are comparatively low most of the year except in June. This results from a differing pattern in the AMDs: While in AWARE the AMDs peak in April, in AWARE2.0 they peak in December. The AWARE AMD remains negative from June until January.

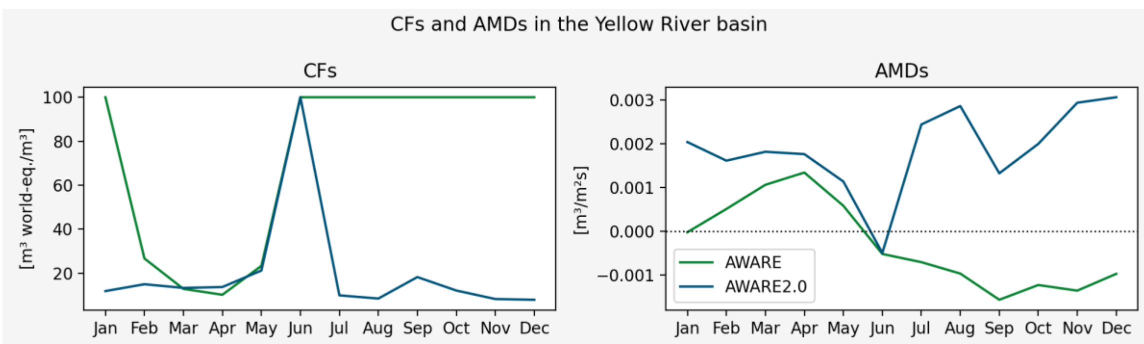

Figure S44: Comparison of monthly CFs and AMDs in the Yellow River basin.

The *AMDs* clearly follow different patterns, which is due to different seasonal patterns of *EWR* and *ActAvail* (Figure S45). While *ActAvail* in AWARE is lowest in June and July and then slowly approaches its peak in January, in AWARE2.0, the low value of June is followed by a sudden increase after which *ActAvail* remains on a plateau for several months. The differing seasonality results from the difference between WaterGAP2 and WaterGAP2.2e output data used in AWARE and AWARE2.0. WaterGAP2.2e seems to better represent the actual streamflow dynamics than WaterGAP2. In the Yellow River basin, streamflow is lowest in summer, but in the second half of the year the monsoon sets in and leads to increased streamflow. This is evident from comparisons with streamflow gauge data for the Yellow River in the lower river reach such as in (Shen et al. 2015, figure 2). Because of better representing the peak flow timing, AWARE2.0 suggests higher *AMDs* in the second half of the year.

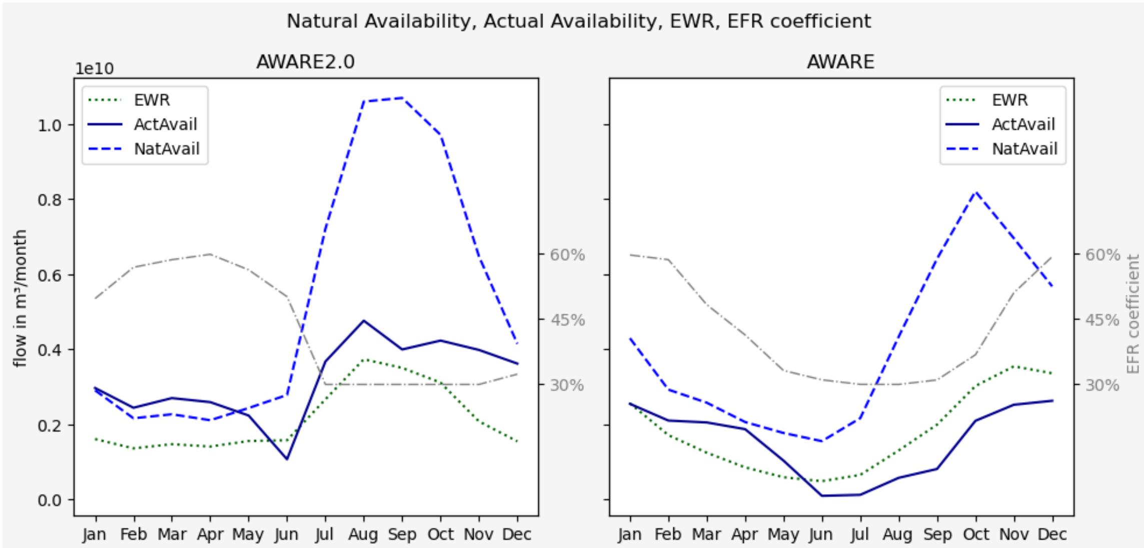

Figure S45: Comparison of ActAvail, NatAvail, EWR and EFR for AWARE and AWARE2.0.

An additional issue leads to the negative *AMDs* in AWARE: Contrary to the mechanics of the VMF method, where EFR coefficients are low in high flow months and high for low-flow months (Pastor et al. 2014), the EFR coefficients in AWARE are not sensitive to the *NatAvail* seasonality. This leads to a situation where low EFR coefficients are allocated to low flow months and high EFR coefficients are allocated to high-flow months. For example, August to January in AWARE are high-flow months according to the classification of the VMF method, but some of them are assigned high EFR coefficients, which leads to an overestimation of the *EWR*. The EFR coefficient for November is 50%, but according to the VMF method it should be 30%. Had this been reflected in AWARE, the November CF would be 24 m³ world-eq./m³ instead of 100 m³ world-eq./m³. Following two reasons are most likely for the mismatch in EFR coefficient: First, it could result from a mismatch in NatAvail data between WaterGAP2 and LPJmL, since the EFR coefficients are taken from EFR output. Second, it could be a result from averaging the EFR coefficients for all grid cells in the watershed. Since in AWARE2.0 all data is taken from WaterGAP2.2e and the EFR is only taken from the outflow grid cell, these issues do not appear there.

S 2.5.1 Impacts on the Chinese country CF

The following paragraphs explain the difference in the country-level CF for China. While in AWARE the CF equals 42.5 m³ world-eq./m³, it equals 22.4 m³ world-eq./m³ in AWARE2.0. The change in CFs for the Yellow River basin occurs similarly in the Hai River basin (Figure S46). Its CF for unspecified water use (weighted by water consumption as described in section S3) changes from 93 to 3 m³ world-eq./m³, the weighted CF of the Yellow River basin from 88 to 30 m³ world-eq./m³. Additionally, the CF of basin 37537 decreases from 69 to 1.8 m³ world-eq./m³ (Figure S47). As shown in Figure S48, these three basins have a strong weight in the calculation of the Chinese country CF. They represent 27% (22%) of the entire Chinese water consumption used for weighting in AWARE (AWARE2.0).

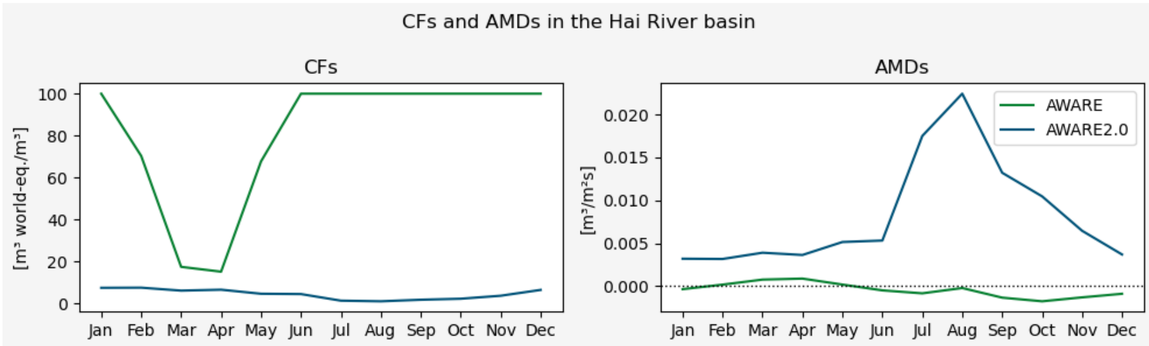

Figure S46: CF and AMD seasonality in the Hai River basin.

The influence of these basins on the Chinese CF can be assessed by removing them from the CF calculations in AWARE and AWARE2.0. This reduces the CF of AWARE by more than one third, but only moderately increases the CF for AWARE2.0 (Table S4). It is therefore safe to say that changes in these three watersheds highly influence China's CF and the difference between AWARE and AWARE2.0. The changes are however not resulting from the implementation changes studied in the sensitivity analysis: We recalculated the original AWARE CFs by simply changing the model from WaterGAP2 to WaterGAP2.2e and recalculating the basin-averaged EFR percentages from the WaterGAP2.2e data instead of using the data of LPJmL, leaving the remaining methodology as in original AWARE. This as well leads to a China CF that is much lower than in AWARE (21.9 m³ world eq./m³). We call this sensitivity scenario AWARE2.0$_{rollback}$ (Table S4). This allows the general statement that the change in China's CFs is rather prompted by the hydrological input data than by other changes in the update. There are a multitude of possible reasons for this finding, most notably the WaterGAP model version and the used climate forcing. Further information on the impact of both aspects on discharge simulations of large rivers can be found in the Supplementary Material of Müller Schmied et al. (2024) (figures S56-S58), albeit not using the model version that was used for AWARE.

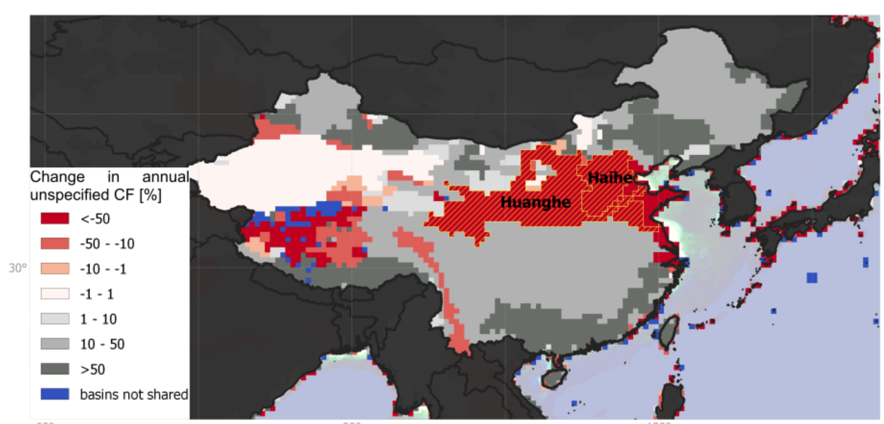

Figure S47: Change in annual unspecified CFs between AWARE and AWARE2.0. The Yellow River and Hai River basins, and basin 37537 (all highlighted with yellow line pattern) show a strong decrease in CFs; the same applies for several endorheic basins in the Tibet Province.

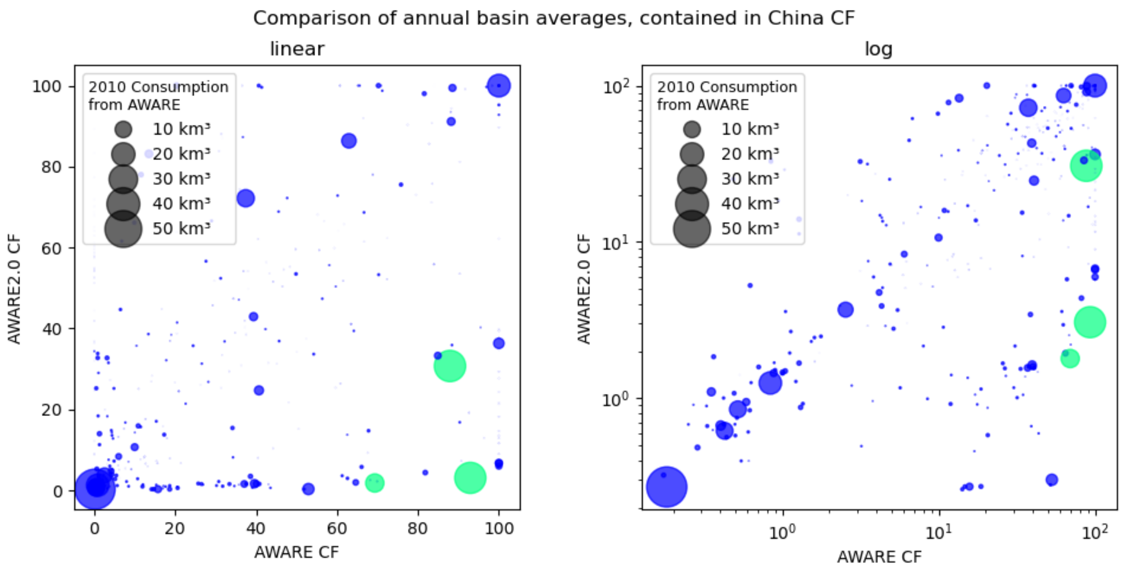

Figure S48: Scatter plot of annual basin values contributing to the CF of China, dot size according to weight in the spatial aggregation.

Table S4: Different country CFs of China depending on basins included and input dataset used.

	CF of China for unspecified water use [m³ world-eq./m³]
AWARE	42.5
AWARE without Yellow River etc.	25.3
AWARE2.0	22.4
AWARE2.0 without Yellow River etc.	24.0
AWARE2.0$_{rollback}$	21.9

S 2.6 Impact of using aHWC instead of pHWC

The scenario analysis in the main paper does not include a separate scenario for the change in the calculation of the AMD_{world_avg}, since it has a relatively straightforward effect on the CFs: The use of aHWC instead of pHWC for the calculation of the AMD_{world_avg} leads to an increase in the AMD_{world_avg} and thus in the CFs by 8.6%. This increase applies to almost all basin CFs. Consequently, basins which with pHWC had a CF of 90 m³ world eq./m³ now equal 97.7 m³ world eq./m³. While this does not impact comparative LCIA results for most of the basins, it increases differentiation at the lower end (two CFs that both were 0.1 m³ world eq./m³ now might be 0.104 and 0.108 m³ world eq./m³, respectively) and decreases differentiation at the upper end of the AWARE CFs (two CFs of 94m³ world eq./m³ and 98 m³ world eq./m³ now might both be 100m³ world eq./m³).

For basins which are affected by the upper or lower cut-offs before or after the increase, the increase can be less, down to 0%. This increase is not random. From 2010 to 2019, when switching from pHWC to aHWC, the AMD always increases between 4.8% and 9.3% (Figure S49).

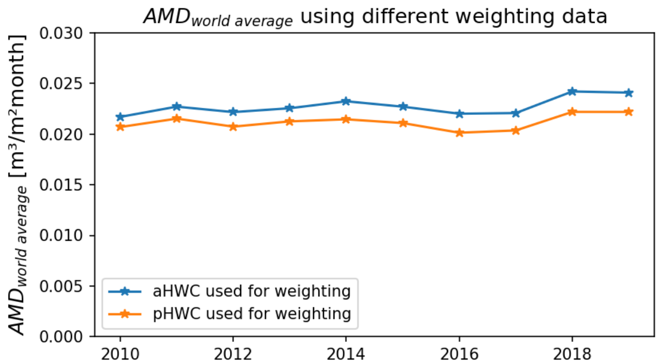

Figure S49: The $AMD_{world\ avg}$ depending on the type of water consumption (aHWC, pHWC) used in its calculation, retrieving the weighting data from the years 2010 to 2019.

S 3 Aggregated Characterization Factors

The native CFs of AWARE2.0 were aggregated to country and annual CFs, similar to the aggregations for (Boulay et al. 2018). For weighting the native-scale CFs, potential water consumption (*pHWC*) of 2019 on grid cell level was used, subject to the extrapolation and scaling described in Supporting Information S2, chapter S3. Aggregations were done for three water use cases: Irrigation, non-irrigation and unknown use. Contrary to Boulay et al. (2018), the water demand in m³ is not assumed to be equal every month for non-irrigation use, but adheres to the number of days per month, thus improving the temporal representativity of the aggregated CFs.
The annual CFs on basin level for all three types of water use are shown in Figure S52.
For the country aggregations, first the *pHWC* of each grid cell was allocated to each country according to Figure S50. The *pHWC* on grid cell level for each country was then used to weight the grid cell's native CF in the averaging to country level (Figure S53).

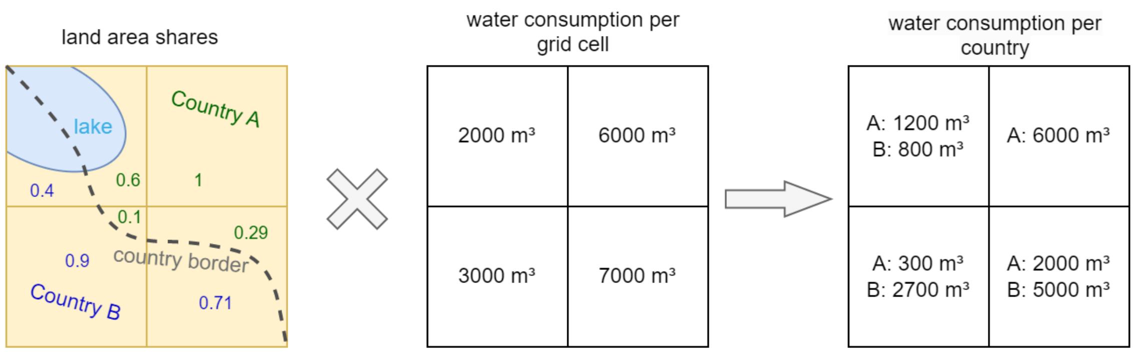

Figure S50: For each country, area share per grid cell was determined, discarding major lake areas. The area shares were applied to pHWC on grid cell resolution, resulting in water consumption shares per country in each grid cell.

S 3.1 Comparison between indicators

The comparison of AWARE and AWARE2.0 country CFs shows that the most relevant changes in annual CF occur for smaller countries, e.g. Bahrain or Cabo Verde (Figure S51). However, also China changes its rank by more than 30 places. The rank correlation coefficient is 0.9. In comparison with ranks obtained by the water scarcity LCIA indicators "Water Stress Index" (WSI) (Pfister and Bayer 2014; Verones et al. 2020) and "WAVE+" (Berger et al. 2018), neither AWARE nor AWARE2.0 clearly correlate better (Figure S54). For these comparisons, the rank correlation coefficient is between 0.6 and 0.8. Depending on the country ranking in the WSI and WAVE+, AWARE2.0 ranks can sometimes be much higher than one while being lower than the other (see for example Angola in Figure S55). The main conceptual difference between AWARE and the other indicators are the consideration of environmental water requirements in AWARE and the main hypothesis of how to express the water scarcity level: In the WSI and WAVE+, the starting point is a ratio between water demand (withdrawal or consumptive) and the renewably available water, while in AWARE a difference between available water and water demands is set into relation to the area of a watershed (Berger et al. 2018). Correlations of AWARE2.0 and AWARE with endpoint indicators are even lower than the correlation with midpoint indicators (Figure S56). This is expected since endpoint indicators consider the vulnerability of humans or ecosystems through aspects such as water supply infrastructure, while the midpoint indicator AWARE2.0 disregards these aspects.

Besides the conceptual difference in the indicators, differences could also result because of differing input data characteristics, such as the temporal period assessed, or the global hydrological model and the aggregation technique used. This paper, however, focuses on the differences between AWARE and AWARE2.0.

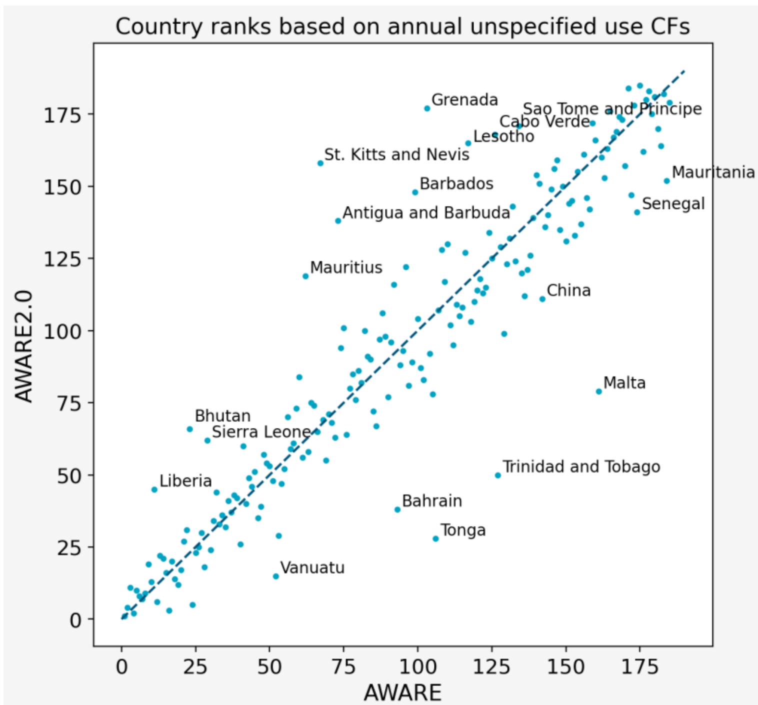

Figure S51: Comparison of 185 annual unspecified country CFs for AWARE and AWARE2.0 according to their global rank (high rank equals high CF). Labeled countries differ in rank by more than 30 places. The rank correlation coefficient is 0.93.

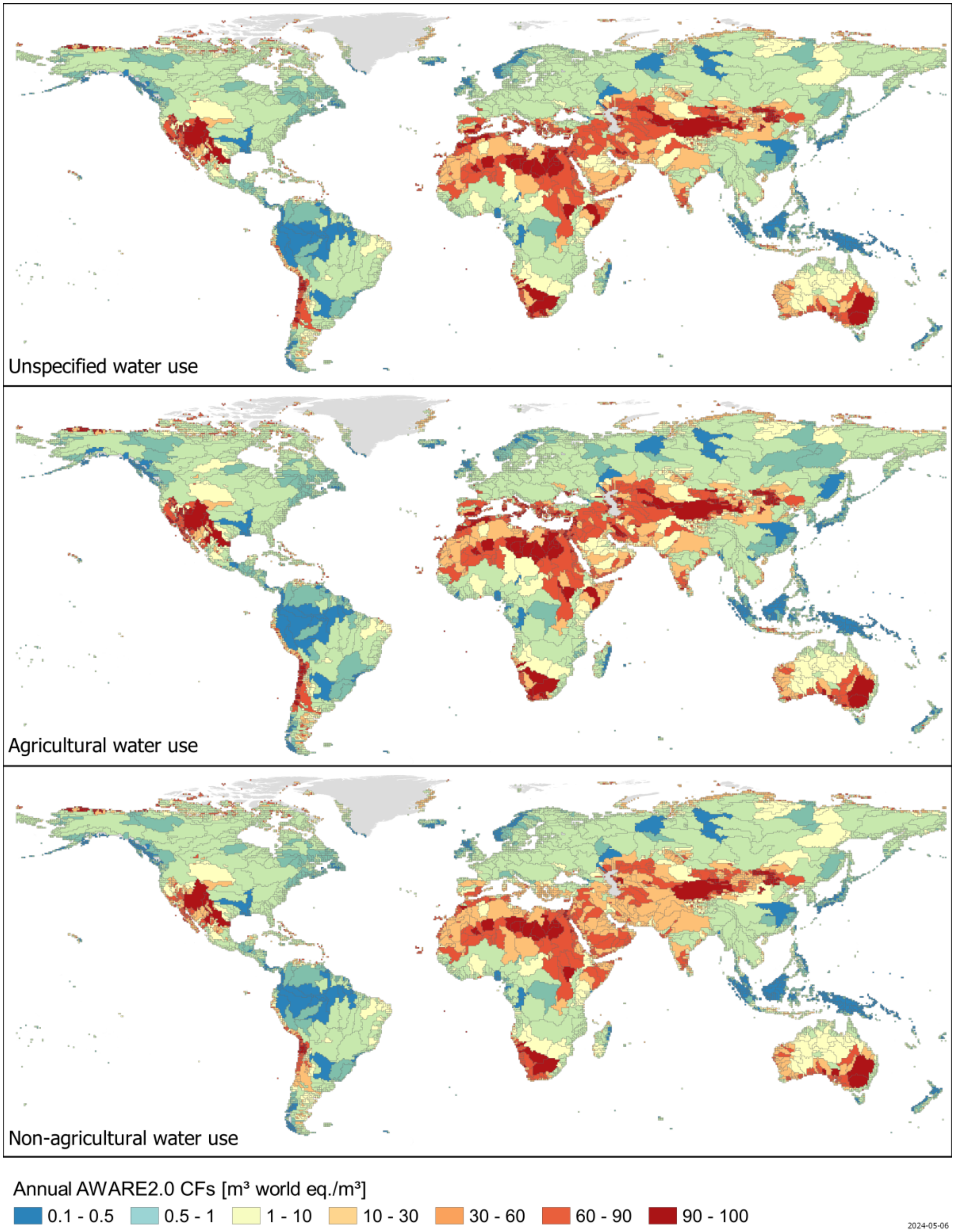

Figure S52: Annual AWARE2.0 CFs on basin level for all 9406 covered basins.

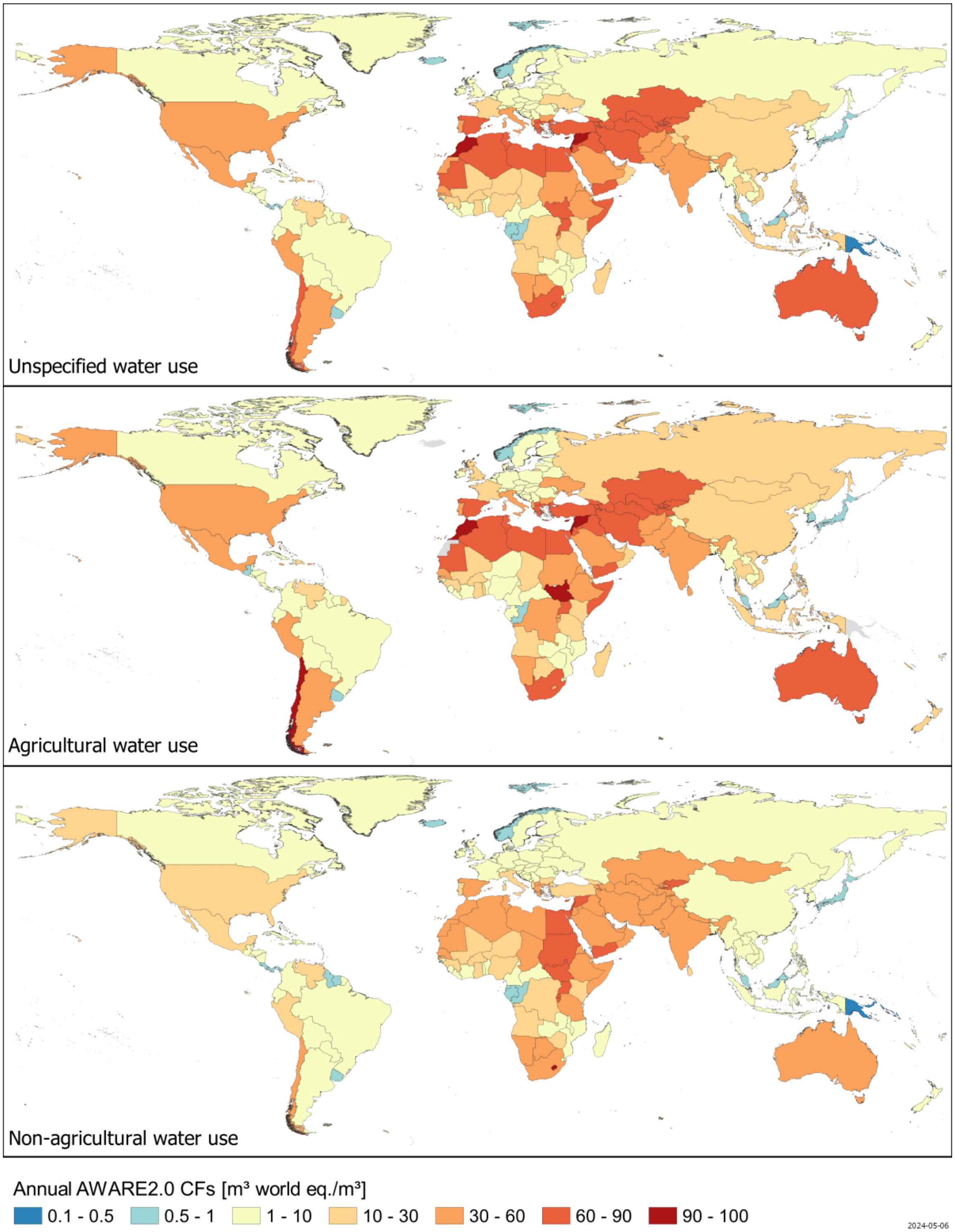

Figure S53: Annual AWARE2.0 CFs on country level. The country delineations of GLAM (Global Guidance for Life Cycle Impact Assessment Indicators and Methods) are used. Overseas territories (e.g., Greenland) are not separated from the mainland (e.g., Denmark).

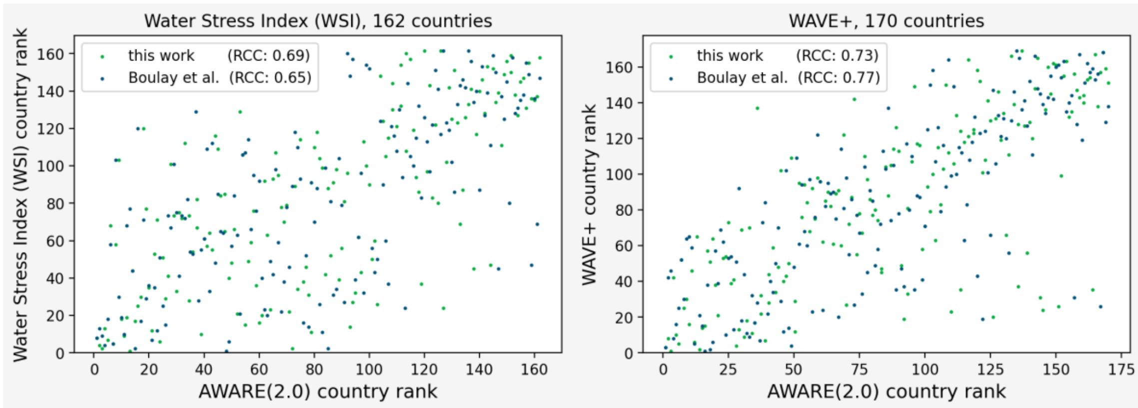

Figure S54: Comparison of AWARE2.0 and AWARE (Boulay et al. 2018) country ranks with ranks of the Water Stress Index WSI as provided with LC-IMPACT (Pfister and Bayer 2014; Verones et al. 2020) and with WAVE+ (Berger et al. 2018). RCC: Spearman's rank correlation coefficient.

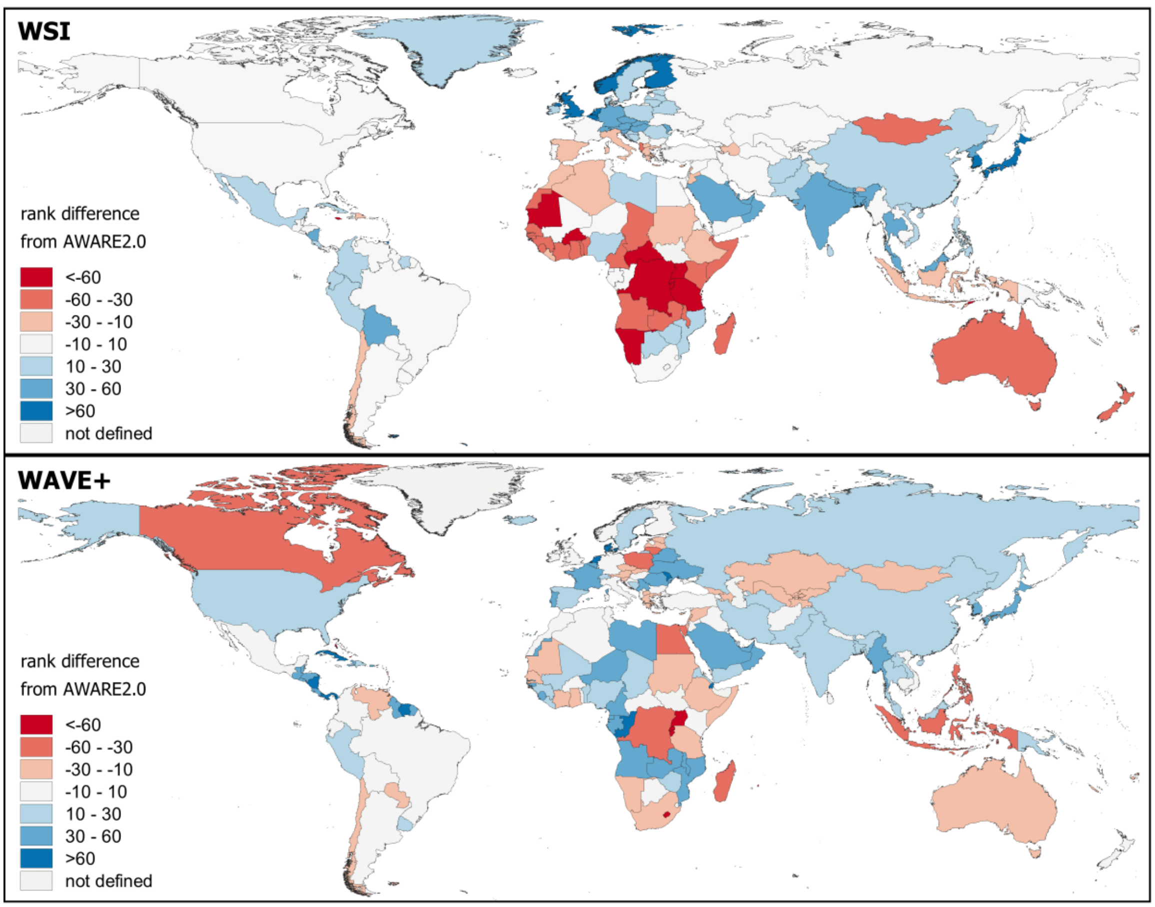

Figure S55: Difference between AWARE2.0 (Boulay et al. 2018) country ranks and country ranks of the WSI as provided with LC-IMPACT (Pfister and Bayer 2014; Verones et al. 2020) and of WAVE+ (Berger et al. 2018). Red indicates countries with a higher rank in AWARE2.0.

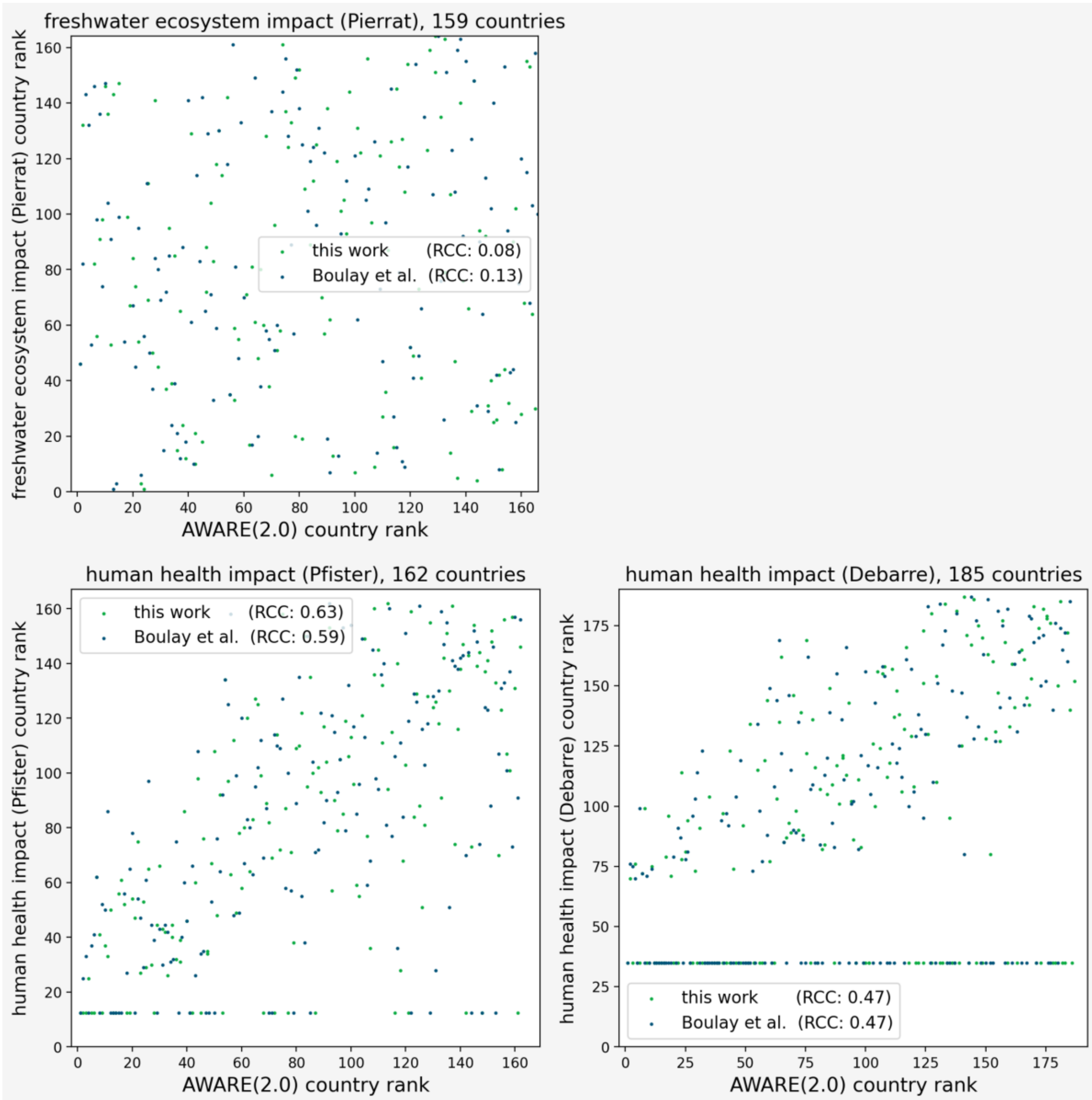

Figure S56: Comparison of country ranks of endpoint indicators for water consumption with AWARE2.0 and AWARE: Freshwater ecosystem impacts (Pierrat et al. 2023) and two indicators for human health impacts, Debarre (Debarre et al. 2022) and Pfister as provided with LC-IMPACT (Verones et al. 2020; Pfister and Hellweg 2011). The horizontal grouping in the human health impact indicators results from countries with sufficient infrastructure to avoid human health impacts of water consumption.

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