Water Through Time: Reconstructing and Projecting Sectoral Water Withdrawals and Consumption from 1970 to 2100

Khan Zarrar, Ioan Sabin Taranu, Wim Thiery, Hannes Müller Schmied, Yoshihide Wada

Historical reconstruction of national and subnational water use (1970-2020)

Available historical datasets and the harmonization process to follow:

FAO AQUASTAT national statistics span 1964-2020 and encompass sectors such as agriculture, industry, irrigation, municipal, livestock, thermoelectric plant cooling, and total water usage. However, these estimates only account for withdrawals, not consumption.

USGS data, covering 1950-2015, is reported every five years at state and county levels. It includes domestic, industrial, livestock, mining, and irrigation sectors, with information on both withdrawals and consumptive use.

To harmonize these datasets, we can adopt the approach outlined by (Liu et al., 2016). In their study, they replaced AQUASTAT US national data with USGS data at subnational level, while keeping the original data for the remaining countries. To fill the gaps in the water use datasets, they employed techniques such as inverse distance weighting, nearest neighbor, and linear interpolation/extrapolation based on associated variables (e.g., irrigated land area, industrial value added, and population). The filling process depends on the number (Navail) and value (Vavail) of available data points within 5-year periods (e.g. 1970-1975 to 2015-2020, in our case), as well as the nature of different variables. For a comprehensive understanding of their approach, refer to the supplementary materials in Li et al. (2016).

It may also be possible to review the approach from (Liu et al., 2016) and look for possible alternative approaches to fill missing data. It may also be interesting to try to obtain access to other subnational water usage datasets if such exists.

Resulting Database:

The resulting database should include national and subnational (US only) water withdrawal estimates for each sector: domestic, livestock, thermoelectric, manufacturing, mining, and irrigation.

For consumptive water use estimates, we can follow the approach in (Huang et al., 2018). For irrigation, this involves applying a correction factor to consumption generated by four Global Hydrological Models (GHMs) like WaterGAP, LPJmL, H08, and PCR-GLOBWB. Domestic, thermoelectric, and manufacturing consumptive use estimates are based on fractions from (Flörke et al., 2013). For mining, the ratio of consumption to withdrawal is assumed to be the same everywhere, as the one documented for the US in USGS.

An important question is whether to estimate consumption at the national level or after spatial downscaling of withdrawal data at the grid cell level? To answer this, we may need to consider the proxy data we use, as domestic consumption to withdrawal fractions may be constant within a given country in the (Flörke et al., 2013) study, but not for irrigation, where local evapotranspiration losses can significantly vary, or for thermoelectric sector, where in the same study, the authors also considered the power plant type (PT), and installed cooling system (CS) of each powerplant (total of 14 possible combinations of PT and CS, each with its own consumption use intensity).

When it comes to livestock, in their study, (Huang et al., 2018), estimated livestock consumption based on data from US alone (USGS), resulting in a constant ratio of 0.4 of consumption to withdrawal everywhere. On the other side, most GHMs assume livestock to be 100% consumptive use. In practice, the consumptive use will depend on the production system – intensive vs extensive.

We can try to improve previous methods, by accounting for the distribution of intensive vs extensive production systems inferred from livestock distribution (see Fig. 1) and livestock water requirements (see Fig. 2). The following algorithm is proposed:

1) Assume all chicken, pig, and duck production follows an industrial/intensive approach.
2) For cattle, buffaloes, sheep, goats, and horses, assume a mixed approach. Identify the fraction of intensive vs extensive production by adding all these animals together and counting the number of heads per square km. Low density indicates extensive systems, while high density indicates intensive systems (Rust, 2019). Establish thresholds. From this step we should get two ratios: $FracMixed_{Intensive}$ and $FracMixed_{Extensive}$, such that the sum of the two equals 1.0.
3) For each grid cell, estimate water use share ratios for each of the 3 groups: purely intensive, mixed intensive, and mixed extensive. To do so, compute the total water abstraction for each livestock type (e.g. cattle, sheep, chicken) based on available data assuming mean annual local temperatures (e.g., see Fig. 2 and Fig. 4 for the relationship between water demand and temperature for different livestock types). We note this terms as:

(Eq1) $Withd_{Intensive} = Withd_{Chiken}(Temp) + Withd_{Ducks}(Temp) + Withd_{Pigs}(Temp)$

(Eq2) $Withd_{MixedIntensive} = \Big(Withd_{Cattle}(Temp) + Withd_{Buffaloes}(Temp) + Withd_{Sheep}(Temp) + Withd_{Goats}(Temp) + \ Withd_{Horses}(Temp)\Big) * FracMixed_{Intensive}$

(Eq3) $Withd_{MixedExtensive} = \Big(Withd_{Cattle}(Temp) + Withd_{Buffaloes}(Temp) + Withd_{Sheep}(Temp) + Withd_{Goats}(Temp) + \ Withd_{Horses}(Temp)\Big) * FracMixed_{Extensive}$

Then the water use share ratios are:

(Eq4) $WatUseRatio_{Intensive} = \frac{Withd_{Intensive}}{Withd_{Intensive}+Withd_{MixedIntensive}+Withd_{MixedExtensive}}$

(Eq5) $WatUseRatio_{MixedIntensive} = \frac{Withd_{MixedIntensive}}{Withd_{Intensive}+Withd_{MixedIntensive}+Withd_{MixedExtensive}}$

$$\textbf{(Eq6)}\ WatUseRatio_{MixedExtensive} = \frac{Withd_{MixedExtensive}}{Withd_{Intensive}+Withd_{MixedIntensive}+Withd_{MixedExtensive}}$$

4) Assume consumptive fractions for each system (e.g., $Coeff_{Extensive} = 1.0$ for extensive systems and $Coeff_{Intensive} = 0.3$ for intensive systems). For the US, the estimate is about 0.4, so it is possible to adjust the thresholds to match this value based on estimate US profile of intensive vs extensive in step (2), such as:

$$\textbf{(Eq7)}\ 0.4 = \frac{1}{N_{GridcellsInUS}} * \sum_{g=1}^{N\_GridcellsInUS} (Coeff_{Intensive} * WatUseRatio_{Intensive} + Coeff_{Intensive} * WatUseRatio_{MixedIntensive} + Coeff_{Extensive} * WatUseRatio_{MixedExtensive})$$

5) Finally, we can transform the withdrawal estimate at gridcell level into consumption by multiplying by the coefficients obtained in the step (4).

$$\textbf{(Eq8)}\ Cons_{grid}^{livestock} = \left(Coeff_{Intensive} * WatUseRatio_{Intensive}^{grid} + Coeff_{Intensive} * WatUseRatio_{MixedIntensive}^{grid} + Coeff_{Extensive} * WatUseRatio_{MixedExtensive}^{grid}\right) * Withd_{grid}^{livestock}$$

Here is an example of how the algorithm would work in practice.

Step 1-2: For given gridcell, we have the expected livestock withdrawal, but also the number of livestock for each group (e.g. chicken, pigs, and other animals from GLW datasets).

Step 3: When we look at the distribution of mixed livestock system (e.g. horses, cattle, sheep, etc.), we find about 0.5 heads per square km. Based on estimated thresholds (to be defined), this is rather low density, and we estimate that for this density 0.9 fraction of animals are on extensive system (e.g. pasture), and 0.1 on intensive system (e.g. industrial milk cows). We compute the total water withdrawal of each livestock in the gridcell to find that 40% is used by the purely industrial group (chicken, pigs, etc.) and remaining 60% by the mixed system (cattle, horses, etc.).

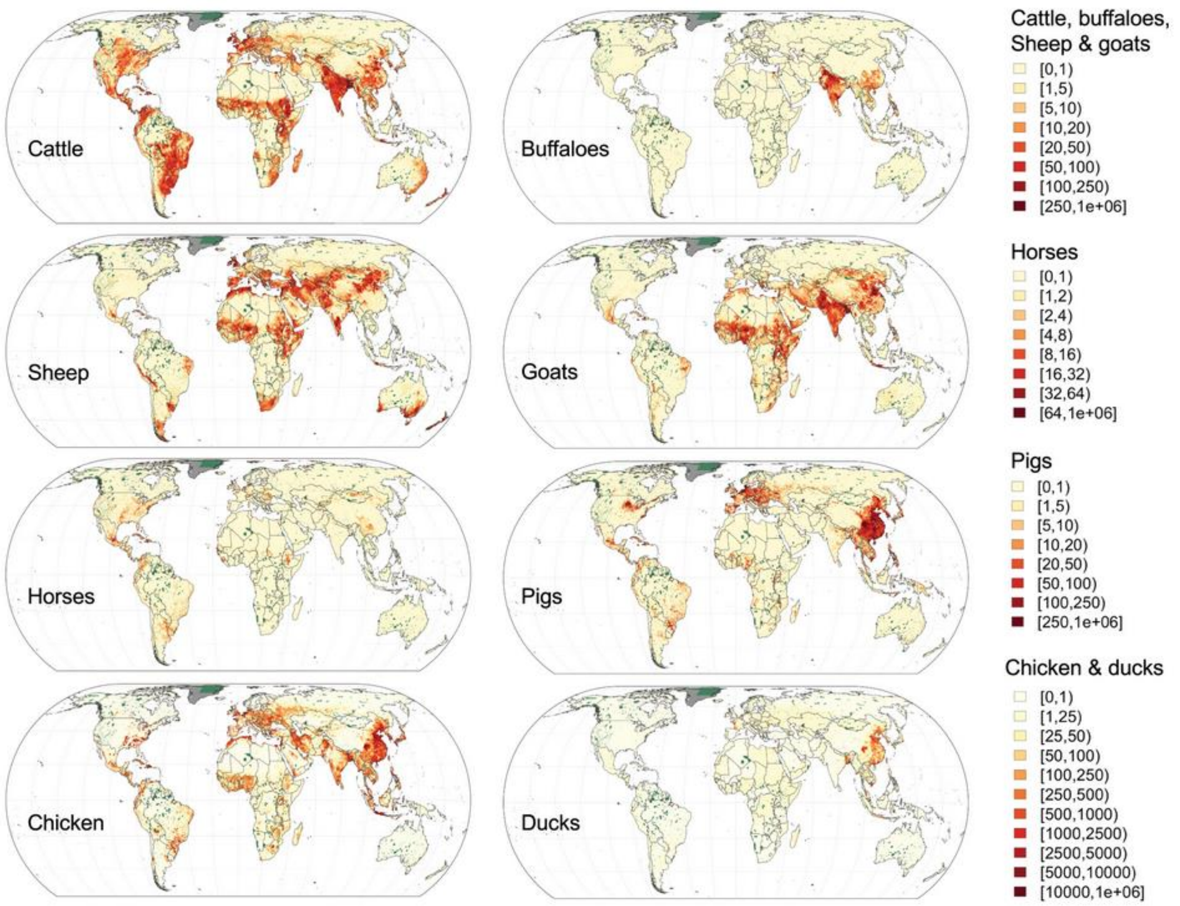
Step 4-5: We compute the gridcell livestock consumption based on our estimates for intensive vs extensive system:

$$\textbf{(Eq9)}\ Cons_{grid}^{livestock} = (0.3 * 0.4 + 0.3 * (0.1 * 0.6) + 1.0 * (0.9 * 0.6)) * 1000m3 = 678\ m3$$

or 67.8% of total withdrawal for this given cell is consumed, so 27.8% more compared to the universal value in (Huang et al., 2018), by simply recognizing the partially extensive character of the local livestock production.

Taking into account that this methodology to estimate consumption rates for livestock sector can be done at gridcell level. We should do this procedure only after spatially downscaling livestock withdrawal.

From: Global distribution data for cattle, buffaloes, horses, sheep, goats, pigs, chickens and ducks in 2010



Dark grey are areas considered unsuitable and dark green areas correspond to IUCN protected areas.

Figure 1 Overview of the Gridded Livestock of the World (GLW 3) data sets for cattle, buffaloes, sheep, goats, horses, pigs, chickens and ducks. Source: Gilbert et al, 2010.

Spatial and temporal downscaling of the national/subnational database:

For the spatial and temporal downscaling we use a slightly modified approach from (Khan et al., 2023) (it is important to keep consistency between historical and future downscaling, to have continuous time series even at gridcell level). The following changes are proposed:

1. For the temporal downscaling, from yearly to monthly, for domestic and thermoelectric sectors, we compute the modulating/downscaling functions based on ISIMIP3a observation dataset which should increase consistency with the future dataset at the transition period because the future data is already bias-adjusted (see chapter on the future scenarios).
2. We introduce a new temporal downscaling algorithm for livestock sector (see proposed algorithm below)
3. For spatial downscaling of thermoelectric sector, actual power plants locations will be used.

Things to check:

- Should we also produce a counter-factual water demand? To do so, for example for domestic, electric and livestock sectors, we could keep the same annual amounts but update the modulating/temporal downscaling functions. Since in the counter-factual climate for a given gridcell, the gaussian distribution for temperature of the counterfactual will be shifted and with shorter hot tail, we can potentially expect the resulting monthly data based on counterfactual climate to have less pronounced peaks, and water demand being distributed more evenly throughout the year. For irrigation, we would need to use ISIMIP3a simulations with adjustments being likely required on both seasonality and total withdrawal.

Temporal downscaling for livestock sector:

From (Steinfeld et al., 2006) we have the following water use intensity for different types of livestock, based on temperature:

Table 4.2

Drinking water requirements for livestock

Species	Physiological condition	Average Weight	Air temperature °C 15	25	35
			Water requirements		
		(kg)	*(.......... litres/animal/day ....)*		
Cattle	African pastoral system-lactating – 2 litres milk/day	200	21.8	25	28.7
	Large breed – Dry cows – 279 days pregnancy	680	44.1	73.2	102.3
	Large breed – Mid-lactation – 35 litres milk/day	680	102.8	114.8	126.8
Goat	Lactating – 0.2 litres milk/day	27	7.6	9.6	11.9
Sheep	Lactating – 0.4 litres milk/day	36	8.7	12.9	20.1
Camel	Mid-lactation – 4.5 litres milk/day	350	31.5	41.8	52.2
Chicken	Adult broilers (100 animals)		17.7	33.1	62
	Laying eggs (100 animals)		13.2	25.8	50.5
Swine	Lactating – daily weight gain of pigs 200g	175	17.2	28.3	46.7

Sources: Luke (2003); National Research Council (1985; 1987; 1994; 1998; 2000); Pallas (1986); Ranjhan (1998).

Figure 2 Example of water requirements for different livestock types depending on temperature. Source: (Steinfeld et al., 2006).

Based on this we introduce the following approach for temporal downscaling (basically the same as for domestic in Huang et al, 2018, with the only difference in how we compute the R:

(Eq10) $$Withd_{year,month}^{livestock} = \left(\frac{Withd_{year}^{livestock}}{12}\right) * \left(\frac{Temp_{year,month} - Temp_{year}^{average}}{Temp_{year}^{max} - Temp_{year}^{min}} * R + 1\right)$$

Assuming that we have a gridcell with the following properties:

- $Withd_{year}^{livestock}$ = 1200 m3
- $Temp_{year,month}$ = [6, 7, 10, 14, 18, 21, 23, 23, 19, 15, 10, 6] (monthly mean temperatures from January to December in degrees C)

Than depending on different R values we can get the following possible monthly distribution of withdrawals (see Fig. 3). It is important to notice here that both extremes of possible R values (R=0 and R=2) are not really realistic, so may need to think of a way to constrain the possible range of R values.

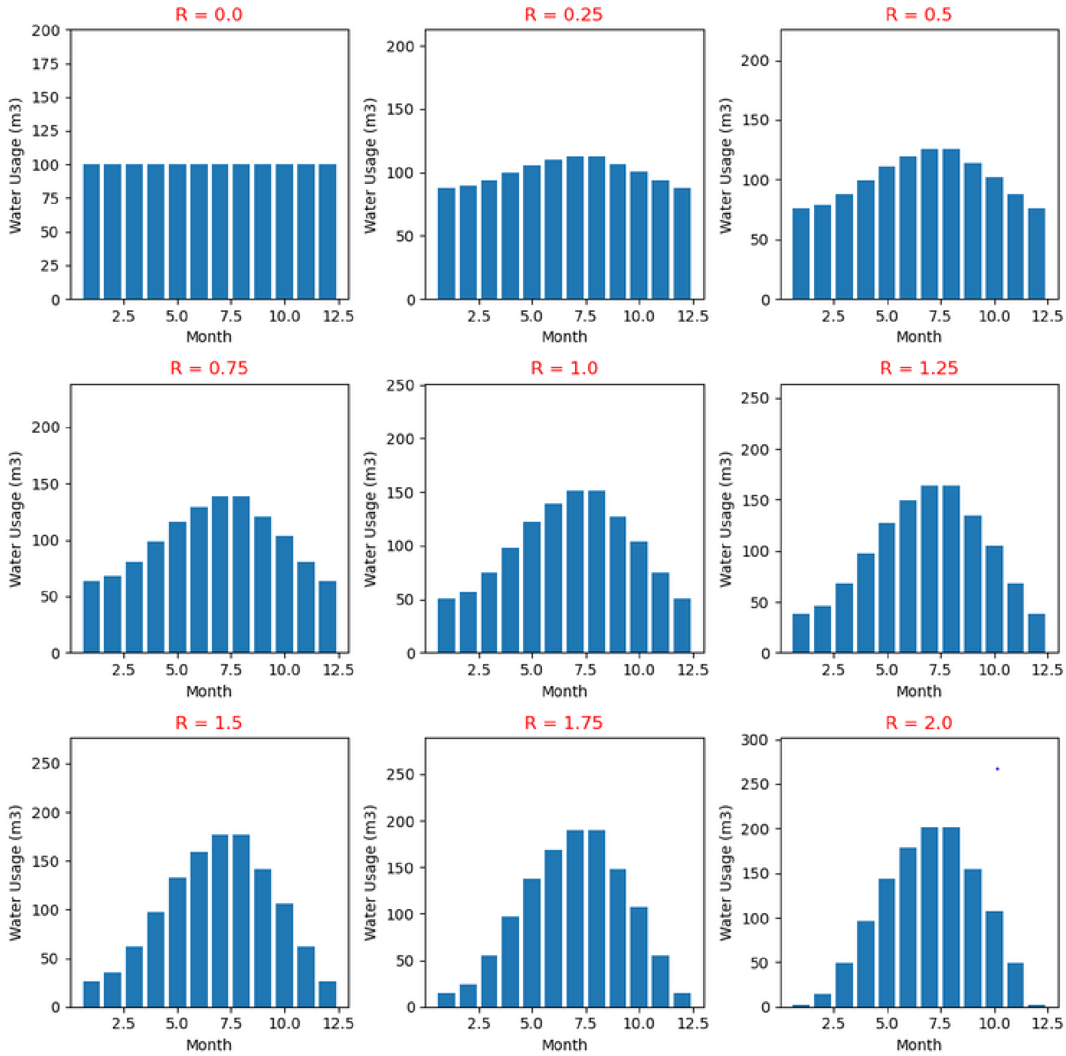


Figure 3 Based on a total annual livestock withdrawal ($Withd_{year}^{livestock}$) and provided temperature range throughout the corresponding year ($Temp_{year,month}$) we can this temporal downscaling by applying Eq. 10 for different R values.

Usually, we would try to tune R based on our reference data for countries or specific locations. At the moment, there is no such reference dataset with monthly estimates of livestock withdrawals by country or region. Therefore, we will introduce an estimation of R for each gridcell, based on our process understanding, which is that each cell is populated with a certain number of different types of livestock (e.g. X cattle, Y chicken, Z pigs, etc), and that each of these livestock may be more or less sensitive to temperature variations.

Based on data from Steinfeld et al. (2006) we get the following temperature sensitivities for different livestock types:

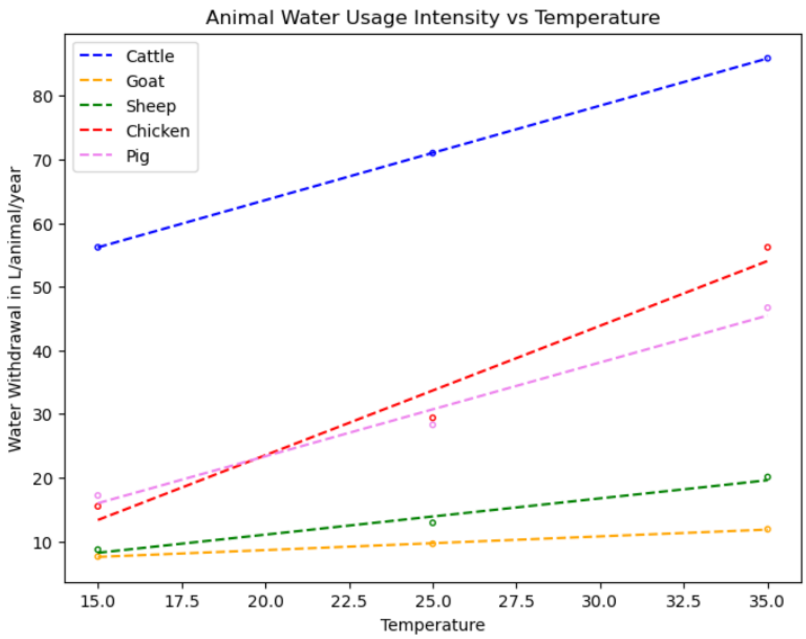


Figure 4 Linear interpolation of the available data on different livestock water use depending on the temperature. The actual best fit is not necessarily known, especially outside the available reference range (from 15 to 35 degrees), so this linear interpolation can be seen as a temporary best guess.

Using the information about the number of each livestock type, and the annual mean temperature, we can estimate a theoretical water use share for each animal type (see Eq. 11). We call this a theoretical water use ratio, because the water usage we estimate this way may not correspond well with the national data we intend to downscale, but despite this, the ratios should be more or less correct, assuming the credibility of the GLW datasets.

(Eq11) $WaterUseRatio^{i}_{livType} = \frac{Number^{i}_{livType} * Withd^{i}_{livType}(Temp_{year})}{\sum^{all\ liv\ types}_{liv\ type\ i} Number^{i}_{livType} * Withd^{i}_{livType}(Temp_{year})}$

Where $WaterUseRatio^{i}_{livType}$ is the ratio between the hypothetical annual water use by livestock *type i* (e.g. chicken) compared to the total annual water use by all present livestock types in the given gridcell; $Number^{i}_{livType}$ is the number of heads for given livestock type, and $Withd^{i}_{livType}(Temp_{year})$ is estimated hypothetical annual water use for a single animal of the given livestock type for given annual mean temperature (to obtain this value, we simply introduce $Temp_{year}$ in the trend lines in Fig above; since we don't have data for temperature below 15 degrees and above 35 degrees, we can simply use the values at the boundaries in such cases; it may be also possible to extrapolate, but it is likely more conservative to stay within known boundaries).

Using these $WaterUseRatio^{i}_{livType}$ and the slopes from the trend lines, we can make some reasonable estimation of R value for given grid:

(Eq12) $R = C + \frac{2}{\pi} \sum^{all\ liv\ types}_{liv\ type\ i} WaterUseRatio^{i}_{livType} * \operatorname{atan}(slope^{i}_{livType})$

Where C is a constant which may be adjusted in the range [0, 1] such that C=0, will reduce the overall difference between the coldest and warmest month, and a C=1 will maximize this difference, while keeping the R value reasonable (< 2); $slope^{i}_{livType}$ is the slope of the trend lines from Fig. 4 and the atan ($slope^{i}_{livType}$) of this slope will give the angle the trend line makes with the horizontal in radians (a higher angle means higher temperature sensitivity and therefore larger resulting R value); by accounting for $WaterUseRatio^{i}_{livType}$ we make each gridcell unique, by recognizing the potential differences in animal production practices and resulting sensitivity to temperatures.

In the following, I use C=1 as an example (see Fig. 5). But it may be important to find a process based approach in trying to estimate this constant. In order to do so, the question we would need to answer is for a given annual livestock water withdrawal at gridcell level (obtained from spatially downscaling the national data using GLW), present number of different livestock types in this gridcell and monthly mean temperatures for that year, what is the minimum monthly water requirement which should be assured?

For example, if you look at Fig. 5 for a configuration of 100% chickens, if we use C=1, we get R=1.71. For such a large R value, the water withdrawal for the coldest months can become potentially unrealistically low (<50m3 from an annual demand of 1200 m3 in this case). So, how do we find a realistic lower boundary? A potential approach could be:

Step 1: Compute for each animal present in the gridcell, the annual water withdrawal using the annual mean temperature:

(Eq13) $TotalYearWithd^{i}_{livType} = Number^{i}_{livType} * Withd^{i}_{livType}\left(Temp_{year}\right)$

Step 2: Since the total annual livestock water withdrawal (summed over each livestock type in Eq. 13) will be likely different from our nationally downscaled version $Withd^{livestock}_{year}$, we need to find the adjustment/scaling factor:

(Eq14)

$$ScalingFactor = \frac{Withd^{livestock}_{year}}{\sum^{all\ liv\ types}_{liv\ type\ i} Number^{i}_{livType} * Withd^{i}_{livType}(Temp_{year})}$$

Step 3: Now we can simply estimate the minimum acceptable livestock monthly water withdrawal for the coldest month in the available time series for given gridcell as follows:

(Eq15)

$$MinimumMonthlyWithd^{livestock} = \frac{ScalingFactor}{12} * \sum^{all\ liv\ types}_{liv\ type\ i} Number^{i}_{livType} * Withd^{i}_{livType}(Temp_{coldest\ month})$$

Where we also divide by 12, since the summation will give an yearly estimate, and we are interested in the minimum acceptable monthly value.

Step 4: To compute the constant C, we can now simply find the R value, which would create the monthly distribution, such that the resulting minimum monthly demand will match $MinimumMonthlyWithd^{livestock}$.

Now coming back at the example where C=1. Using Eq. 12, and some theoretical values for $WaterUseRatio^{i}_{livType}$ we can get the following temporal downscaling (see Fig. 5). The advantage of this mathematical formulation is that we never arrive at R = 2 for given slope data (a slope of 90 degrees is required, which is impossible). It also consider the gridcell mix of different livestock types (noted as Ratios here), as well as their individual water requirements. So, for example a gridcell dominated by chicken will much more sensitive to temperature variations, in comparison to gridcell with high presence of goats, sheep or pigs.

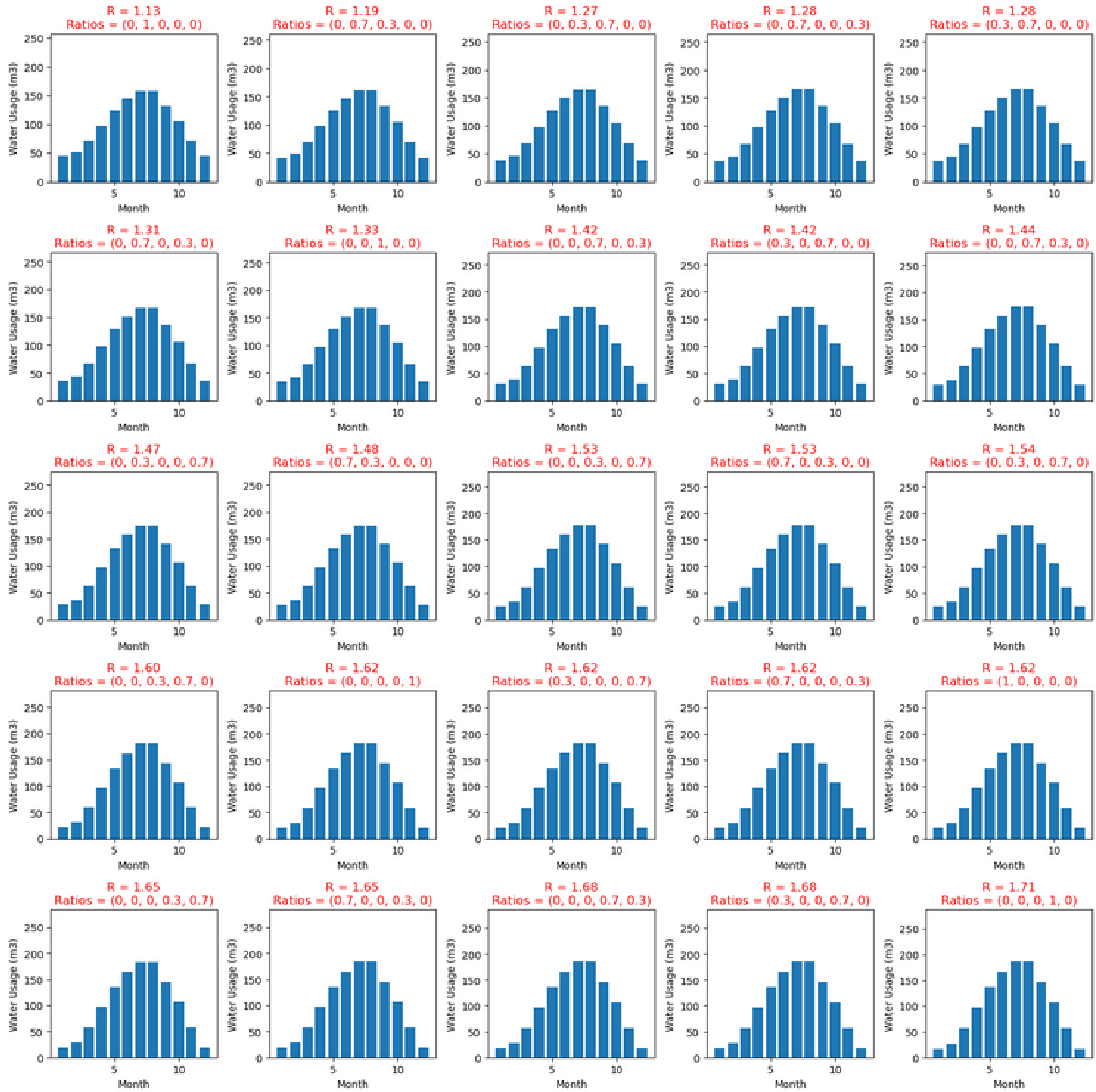


Figure 5 Emerging temporal downscaling for different fractions of animals in the gridcells (Ratios = Fraction(Cattle, Goat, Sheep, Chicken, Pig)), and provided monthly temperature values.

Another important advantage, is that the downscaling is sensitive to temperature fluctuations. For example, if we assume a year with anomalous hot April, the resulting temporal downscaling will take this into account (see Fig. 6). This kind of temperature sensitivity may be very interesting and relevant to better highlight the impact of anomalous hot months on water security. In the context of livestock specifically, this approach may facilitate further work on predicting and projecting livestock mortality for example.

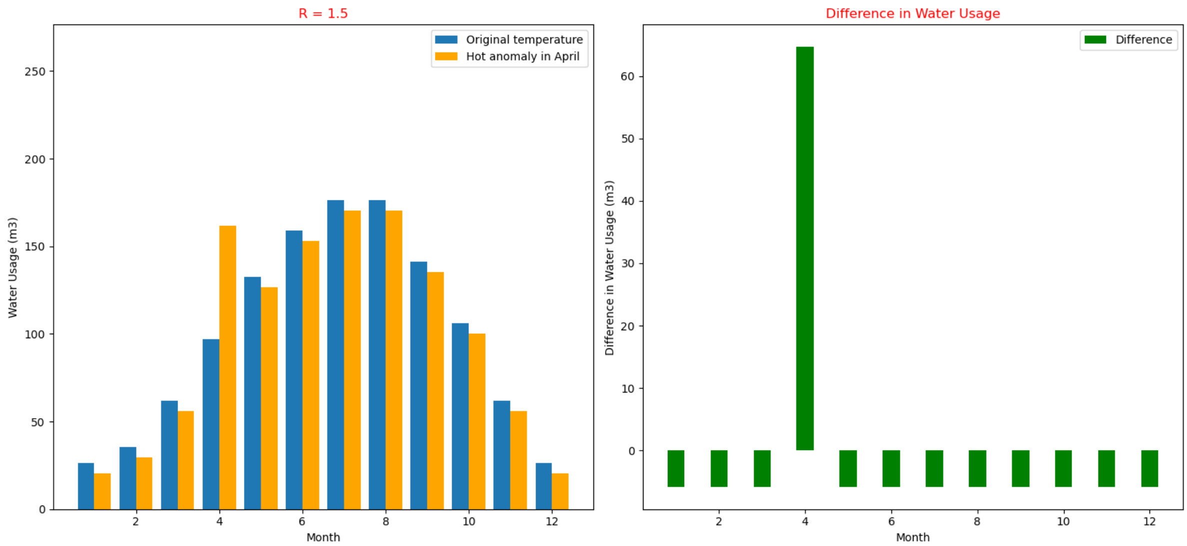


Figure 6 Representation of how the temporal downscaling will be affected by an anomalous hot April. Here we increased, the April mean temperature from 14 to 22 degrees Celsius. As a result the demand is higher in April in comparison to the original temperature data, while the total annual demand is kept constant, as the additional demand in April is compensated by decrease for other months.

Future scenarios on water use (2010-2100)

When it comes to computation of future water demands, we rely on the same infrastructure as in(Khan et al., 2023), with a few small changes and improvements (see Fig. 3):

1. As climate data we use the bias adjusted GCMs data prepared for the ISIMIP3b protocol, for SSP1-RCP26, SSP3-RCP70 and SSP5-RCP85 scenarios.
2. In the past studies, temporal downscaling of domestic and electric sectors was done using the modulating functions derived from historical observations. Then same modulating function is used to downscale any year data including for the future, without considering the changes in the relative hotness or coldness of each month in the corresponding year window. We propose to improve this approach by updating the modulating function for each individual year and match it with the driving climate data. This additional step may complicate to some extent the downscaling process, but there is definitely some added value compared to previous research. While this method will not change the total cumulated withdrawal for the affected sectors for any given year, it will change the intra-annual distribution of values, making the distinction between hotter and colder months within one year more distinct. This additional sensitivity to anomalous weather, can prove beneficial to better assess the role of climate change on water security.
3. We propose a new temporal downscaling algorithm for livestock sectors. While in the reconstruction by (Huang et al., 2018), there is no intra-annual dependence on water demand by livestock sector, there is enough literature to support the opposite, with

livestock water demand depending a lot on the temperature to which they are exposed. The new algorithm takes into account this dependency for each major livestock group. Not only this improvement will make livestock water demand modelling closer to the reality, in the future this improved dataset may allow to better assess instances of unmet demand for livestock sector and resulting livestock mortality through a higher sensitivity to the driving climate data.

4. In comparison to previous version, the spatial downscaling of electric sector will take into account the actual power-plants locations (previously, population was used as downscaling proxy). Possible data source for this application could be the dataset compiled by the [World Resources Institute.](#)

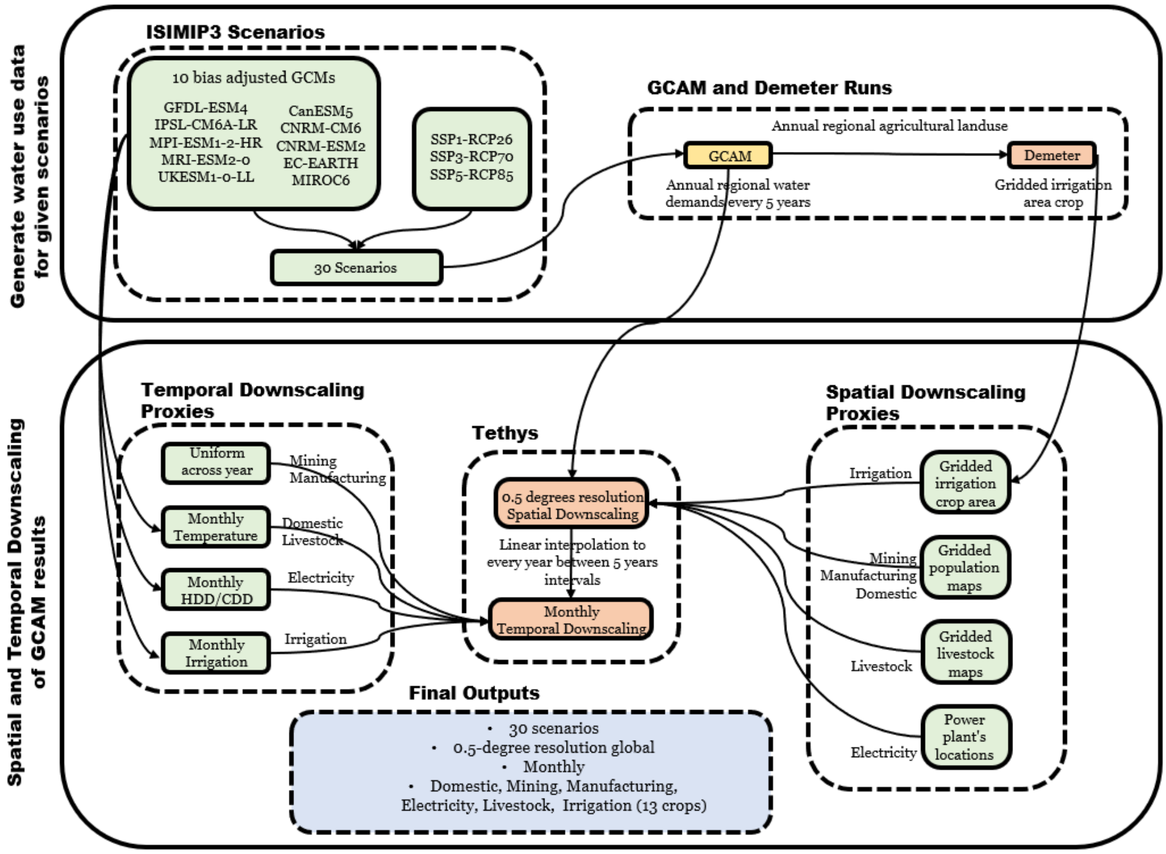


Figure 7 Proposed workflow (figure adapted from Khan et al, 2023). In the first stage, we run the GCAM model using ISIMIP3 bias adjusted GCMs climate data for 3 scenarios: SSP1-RCP26, SSP3-RCP70 and SSP5-RCP85. The water withdrawal and consumption outputs from GCAM model are given at the level of 32 regions for the domestic, mining, power generation, industry, and livestock sectors and for 434 region-basin intersections for the irrigation sector at a temporal frequency of 5 years (see Fig. 4 for example of the regions). To obtain gridded data at 0.5-degree resolution and monthly frequency, Tethys package is used. In this figure, green boxes represent driving/proxy data, orange is for model, red for downscaling processes, and blue for final results.

Harmonization of historical and future water demand datasets:

Having consistency of timeseries at national, but also at gridcell level for water withdrawal and consumptions is of extreme relevance for the data users. Having such consistency, increase the usability of this data, as no additional post-processing manipulation is needed.

By using one single framework for spatial and temporal downscaling, and using consistent historical and future climate forcing (observed climate data from ISIMIP3a for the historical reconstruction and bias adjusted climate data from ISIMIP3b for the future scenarios), we are in an unique position where we can create a truly consistent dataset even at gridcell level.

One challenge we should brace for in anticipation, is that GCAM outputs will likely be off to some extent at regional level (e.g. see Fig. 6 in (Khan et al., 2023)). This is because it may be very difficult to tune this model to produce the right results, as there other sectors except water which are to be considered (e.g. agriculture, energy, economy). So tuning strictly for water demands, may generate a worse representation of other sectors.

But even if we use the same GCAM version as in (Khan et al., 2023), we are still in an excellent position to create a time consistent dataset. Since there is no structural difference between history and future (same temporal and spatial downscaling protocol, with consistent proxies at gridcell level, e.g. climate, population, etc.), we have full justification to apply bias correction at gridcell level at the transition point. This is another reason why it is important that we have a sufficiently long overlapping time between the historical and future data (e.g. 2010-2020 in our case or maybe 2015-2020) so that we can estimate and use, the most relevant bias adjustment technique.

As mentioned in previous paragraph, even before we begin the work, we need to be sure that all driving and proxy data we intend to use for the historical reconstruction and future simulations is consistent at gridcell level to avoid possible complications down the line.

Consistency with ISIMIP3 protocol:

While we can be sure that the data we will generate will be used beyond the ISIMIP, to maximize the synergy with this community we need to be consistent with the input data (e.g. use same GDP, population, climate, etc).

At this moment, not all of the ISIMIP3 input data is hardly defined. This means that ISIMIP could for example use the population and GPD data from PNNL instead of the opposite, but it is important to coordinate this as soon as possible.

Advantages of this dataset:

The advantage of this dataset will be:

1. Consistent in time and space through using the same spatial and temporal downscaling protocol, and consistent proxy data (climate, population, etc.).
2. Extend the historical reconstruction of water usage till 2020.
3. State-of-the-art, using well known and approved methodologies for spatial and temporal downscaling, introducing new algorithms (e.g. process based temporal downscaling for livestock and estimation of consumptive livestock water use), and finally an interesting perspective for future scenarios from a recognized Integrated Assessment Model.
4. Covering multiple SSPxRCPxGCMs futures.
5. More sensitive to monthly temperature fluctuations in present and future.
6. Cover most major water usage sectors.

Bibliography:

Flörke, M., Kynast, E., Bärlund, I., Eisner, S., Wimmer, F., Alcamo, J., 2013. Domestic and industrial water uses of the past 60 years as a mirror of socio-economic development: A global simulation study. Glob. Environ. Change 23, 144–156. https://doi.org/10.1016/j.gloenvcha.2012.10.018

Huang, Z., Hejazi, M., Li, X., Tang, Q., Vernon, C., Leng, G., Liu, Y., Döll, P., Eisner, S., Gerten, D., Hanasaki, N., Wada, Y., 2018. Reconstruction of global gridded monthly sectoral water withdrawals for 1971–2010 and analysis of their spatiotemporal patterns. Hydrol. Earth Syst. Sci. 22, 2117–2133. https://doi.org/10.5194/hess-22-2117-2018

Khan, Z., Thompson, I., Vernon, C.R., Graham, N.T., Wild, T.B., Chen, M., 2023. Global monthly sectoral water use for 2010–2100 at 0.5° resolution across alternative futures. Sci. Data 10, 201. https://doi.org/10.1038/s41597-023-02086-2

Liu, Y., Hejazi, M., Kyle, P., Kim, S.H., Davies, E., Miralles, D.G., Teuling, A.J., He, Y., Niyogi, D., 2016. Global and Regional Evaluation of Energy for Water. Environ. Sci. Technol. 50, 9736–9745. https://doi.org/10.1021/acs.est.6b01065

Rust, J.M., 2019. The impact of climate change on extensive and intensive livestock production systems. Anim. Front. 9, 20–25. https://doi.org/10.1093/af/vfy028

Steinfeld, H., Gerber, P., Wassenaar, T.D., Castel, V., Rosales M., M., Haan, C. de, 2006. Livestock's long shadow: environmental issues and options. Food and Agriculture Organization of the United Nations, Rome.