Supporting Information for
Global expansion of sustainable irrigation limited by water storage

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Box S1: Calculating storage-fed irrigation in the Ganges basin

This box details the calculation of storage-fed irrigation for the Ganges Basin, where 152.8 km³/yr of sustainable blue water are available. Irrigation on irrigated croplands requires 95.6 km³/yr. Yet, there is rainfed cropland where sustainable blue water could be used to expand irrigation. This sustainable expansion of irrigation would consume 9.1 km³/yr, thus total sustainable irrigation would account for a total of $D_{\text{tot}} = 104.7$ km³/yr (see table and figure herein). While annual sustainable blue water exceeds irrigation demand, there is a mismatch between irrigation water demand and water availability. Most blue water is available June to December (blue bars), while irrigation demands are highest January to June (yellow bars). Thus, there is a water surplus from June to January (green bars) and a major deficit from February to June (orange bars). In May, total irrigation demand is 16.8 km³/yr, but only 2.2 km³/yr of blue water are available. Thus, irrigation could draw 2.2 km³/yr, but a water deficit of $\Delta_{\text{tot}}(\text{May}) = 2.2$ km³ - 16.8 km³ = -14.4 km³ remains (and no surplus: $\Delta_{\text{tot}}^+(\text{May}) = 0$.)

Over the year, the deficits from all months with a deficit is $\Delta_{\text{tot}}(B) = -63.8$ km³/yr, and the surplus from all months with a surplus is $\Delta_{\text{tot}}^+(B) = 112.0$ km³/yr. Thus, the total potential for storage-fed irrigation in the basin is $SFI_{\text{tot}} = \min([-63.8], 112.0) = 63.8$ km³/yr. For example, in May agriculture would thus use 2.2 km³ from instantaneous withdrawals, and 14.4 km³ could be storage-fed irrigation (if enough storage is available). The difference between $D_{\text{tot}}$ and $SFI_{\text{tot}}$, 104.7 km³/yr - 63.8 km³/yr = 40.9 km³/yr is how much blue water can be sustainably used for irrigation from instantaneous withdrawals without storage.

### Monthly water balance in the Ganges Basin, and the resulting storage-fed irrigation.

|          | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Total |
|----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-------|
| $Q$      | 7.8 | 0.2 | 0.7 | 1.7 | 2.2 | 7.7 | 26.1| 45.3| 33.0| 14.7| 8.5 | 5.1 | 152.8 |
| $D_{\text{tot}}$ | 7.6 | 13.1| 20.6| 15.8| 16.8| 9.1 | 1.1 | 0.7 | 1.9 | 7.1 | 4.8 | 5.9 | 104.7 |
| $\Delta_{\text{tot}}$ | 0.3 | -12.9| -20.0| -14.1| -14.6| -1.4 | 24.9| 44.5| 31.1| 7.5 | 3.6 | -0.8 | 48.2 |
| $\Delta_{\text{tot}}^+$ | 0.3 | 0.0 | 0.0 | 0.0 | 0.0 | 24.9| 44.5| 31.1| 7.5 | 3.6 | 0.0 | 0.0 | 112.0 |
| $\Delta_{\text{tot}}^-$ | 0.0 | -12.9| -20.0| -14.1| -14.6| -1.4 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -0.8 | -63.8 |

Storage-fed irrigation 63.8
Supplemental Discussion 1: Limitation and priorities for future data and modeling efforts

As pointed out in the introduction, this study aims to provide a global overview for links between agriculture, water sustainability, infrastructure, and food security and thus eventually between human development and nature. To provide a response to these questions, we used state of the art datasets and analysis approaches. Yet, discussing the shortcomings of those data and approaches can be useful to define a research agenda for the future. We herein provide a discussion of, first, the selection of input data sets and potential alternatives and, second, the selection of model assumptions and resulting uncertainties.

Uncertainty in input data. In terms of data, our model uses four key datasets.

1. Data on blue water availability (to determine $Q_{tot}$ and $Q$).
2. Current distribution irrigated and rainfed land.
3. Current crop mixes on agricultural lands and their water demand (2 and 3 are used to determine $D_{cur}$ and $D_{Fut}$).
4. Irrigation storage of current reservoirs (to determine $V_{irri}$) and location of future dams

Blue water availability is derived from ref. (1)’s global estimates derived using a hydrologic model with 50 X 50 km (rescaled to 10 X 10 km) resolution. The model was calibrated to global observations of runoff in large rivers (>10,000 km² drainage area), representing conditions around year 2000. We acknowledge that alternative datasets have been published based on different methods, such as neural networks (e.g., ref. (2)). Newer datasets are calibrated to essentially the same discharge data set as ref. (1), only with slightly longer (i.e., post-2000) time series but only for those gauging stations that are still active post-2000. Thus most of the data used for training those alternative models will be identical to what was used in ref. (1) and we do not expect those data to be significantly different. Using ref. (1) also ensures consistency with a wealth of previous agrohydrologic studies. In this context, it should be noted that ref. (1) has been used in 154 studies in the past 5 years alone (as per Web of Science).

The distribution of irrigated and rainfed croplands and the crop mixes grown on that land are derived from the MIRCA2000 dataset (3). MIRCA2000 contains information on crop mixes and crop yields considering for 126 crops, distinguishing between irrigated or rainfed areas, yields under rainfed and irrigated conditions, and thus data for nearly 99% of all crops worldwide. Since 2000, agriculture has expanded (4). Yet, there are no updated datasets reflecting which of those new agricultural lands are irrigated and which are rainfed, and which crops are grown on them. Alternative crop datasets reflect conditions around 2010 (5) but contain only on 42 crops and miss the distribution of irrigated and rainfed lands and associated yields. As a result, MIRCA2000 is still amongst the most widely used crop datasets to represent current agriculture with 777 citations in total and 430 citations in the past five years (Web of Science).

Performing the herein presented analysis for future conditions of irrigation demand and climate forcing would be ideal and could build on recent research on future crop water demands (6). Yet analysis of links between water storage and food
security for a future climate are limited by the absence of crop calorie yields under changing temperatures and CO$_2$ concentrations. This information is only available for some major crops (typically Corn, Wheat, Rice and Soybean, which represent only a fraction of the global nutritional value from crops).

Data on existing dams, their storage volume, and purpose were derived from the GRAND dataset (7) which reflects conditions around 2010 and includes only large dams. Since then, more dams have been built, and small dams likely contribute to irrigation as well. While mapping smaller dams is an area of active research (8), those datasets do not include any attributes relevant for agrohydrologic analysis, e.g., storage volume or operational purpose. To our knowledge there is no more up-to-date dataset of future dam projects to identify which of the dam projects from ref. (9) might have been already constructed or cancelled.

**Uncertainty in model assumptions:** Our assessment is based on a meso-scale modeling of blue water, without a detailed representation of near-surface hydrologic processes such as direct surface runoff (quickflow), runoff in the unsaturated vadose zone (interflow), percolation to shallow aquifers, and baseflow. Many of those processes cannot be distinguished in a meaningful way in meso-scale hydrologic models (i.e., with several tens of km resolution). For example, most quickflow will percolate after few meters or tens of meters, and most subsurface runoff would be intercepted by a stream in much less than 10 km. While not considering those aspects of the water cycle would be a major limitation for local studies, on a meso-scale this is less relevant, because surface water and shallow groundwater are connected (10), and the delayed contribution of shallow groundwater to streamflow is considered in the underlying hydrologic models.

We also do not consider percolation to deep aquifers, i.e., aquifers without any connections to surface water bodies. If groundwater from these aquifers is withdrawn at rates not exceeding natural deep percolation, these deep aquifers can provide an additional source of water to agriculture. Utilizing that storage sustainably will be important, as 40 % of the world’s irrigation is from groundwater. Yet, most countries do not ensure that rates of withdrawal are matched with rates of recharge and most natural deep aquifers are significantly overdrawn (11). Thus, assessments of sustainable water resources for irrigation do not commonly include deep groundwater resources (12, 13) and we follow that practice in this research. However, studying where deep aquifers recharge naturally at rates that could support irrigation withdrawals sustainably, or can be recharged with managed aquifer recharged, would highlight additional opportunities for storage without the impacts of dammed surface reservoirs (e.g., environmental impacts, water losses from reservoirs).

In certain settings with inefficient irrigation systems (low $\epsilon_{irri}$), high return flows would effectively increase water availability for downstream users, thus increasing the overall amount of stored water that is available to agriculture and reducing the need for dammed storage. Reusing return flows would have a similar effect to increasing irrigation efficiency. Similar to other studies on surface water storage (14), our analysis does not account for irrigation return flows because current meso-scale hydrologic models do not provide the required resolution (14) to assess where and if return flows from irrigated fields and conveyance canals would be available for downstream users, and if quality requirements for, e.g., salinity could be met.
Our assessment of irrigation storage is based on long term monthly averages. Yet, climate phenomena related to, e.g., ENSO events, could increase the need for storage to meet irrigation water demands even in drier than average years. At the same time, cropping systems might adapt to longer term fluctuations in water availability by crop switching. Because crop and water demand data used present a longer-term average, we perform this analysis for average conditions, but the impact of multi-year climate patterns provides an interesting area for future research.

As mentioned in the previous paragraph and highlighted in the discussion, crop switching and changing cropping patterns could be a mechanism to reduce impacts of climate variability on irrigation demand and to reduce mismatches between irrigation storage and irrigation demand. On the one hand, crops which create high irrigation demands in periods of limited water availability could be switched for crops whose water demands align better with blue water availability (thus reducing the need for storage). On the other hand, expanding irrigation could motivate switching to crops with higher irrigation demands or increase the number of cropping cycles per year (thus increasing the demand for storage). Yet, cropping systems are often deeply rooted in the local and regional economies and opportunities for crop switching are subject to major uncertainty. We hence do neither assume that crop switching, nor intensified cropping cycles will occur when irrigation is expanded onto currently rainfed land. Thus, when irrigation is expanded onto rainfed lands, the same type of crops there that is grown today is modelled.

Lastly, we do not make any assumptions on the politic and economic feasibility of irrigation storage and conveyance projects. Our analysis highlights biophysical potentials for storage-fed irrigation, assuming that water conveyance is feasible on the scale of hydrologic basins and that currently rainfed land can be equipped for irrigation. For conveyance we provide some insights into the spatial distribution of water storage anddammed reservoirs in Fig. S8 for the Tigris and Ganges. While such detailed analysis highlight challenges and opportunities on local scales, data for scaling them to a global level are missing (14). It should be noted that the feasibility of future water storage and conveyance will likely change with increasing food demand and progressing depletion of non-sustainable water resources. To conclude, our analysis of storage-fed irrigation does thus not hinge on any assumptions on national or regional political economies that will determine if irrigation projects can be implemented (i.e., if the biophysical potential will translate into an economic potential).

While the selection of data and analysis approaches follows the current state-of-the-art in global agrohydrologic modeling, the discussed aspects highlight opportunities for more detailed studies on local and regional levels. Regarding data, we would like to highlight the urgent need to update existing global crop and hydrologic datasets to provide a consistent basis for assessing the current state of the global food systems.

**Supplemental Methods 1: Probability distribution of irrigation parameters**

Central estimates and parameter distributions for $\epsilon_{irri}, f_{irri}$, and $a$ are derived from previously published data. Here, we describe data sources and the resulting probability distributions for each parameter.
\( \alpha \): regression parameter to estimate the storage of future dammed reservoirs from the tabulated installed capacity. This is required because tabulated data on potential dam sites do only include information on installed hydropower capacity but not on storage (9). It should also be noted that the storage of future dammed reservoirs depends on future design choices, e.g., the height of the dam, which in turn would depend on future demands for water and energy storage. Thus, uncertainty in this parameter is systemic and not because of incomplete information.

Ref. (15) estimated the ratio between installed capacity and reservoir storage for 251 dams as \( \alpha = 3.19 \) with a standard deviation of 8.15. Thus, we assumed that \( \alpha \) is normally distributed with a mean of 3.19 and standard deviation \( SD(\alpha) = 8.15 \). Given that the resulting distribution is very wide, we truncated the resulting distribution at 0 to not allow for negative values. This truncation results in a probability of \( \alpha \leq 0 \) of around 30%. In this case we set \( \alpha \) to 0. Drawing 0-values for any dam represents futures in which that dam is built without usable reservoir (i.e., as run-of-river project) or not build at all.

\( f_{irr} \): fraction of reservoir storage that is released for irrigation. Typically, not all water that is stored in a reservoir can be released for irrigation. This is for engineering reasons (bottom outlets do not allow for full drawdown of reservoirs so that some dead storage remains) and sedimentation (storage is lost in reservoirs as sediment delivered from upstream basins is deposited in the reservoir), but notably for operational reasons. If reservoirs are not operated only for irrigation, but e.g., also for domestic water supply, hydropower, and flood control then not all water can be released for irrigation. If dams are used for flood control, then not all reservoir storage might be filled during month of water surplus to maintain some storage to buffer floods. \( f_{irr} \) is notoriously difficult to estimate because it depends on the unknown operation rules of current and future dams. To overcome this data limitation, we used estimates by Biemans et al. (2011) (16), who estimated that 460 km\(^3\)/yr are withdrawn from irrigation dams in the GRAND dataset. Based on our calculations, dams listed in GRAND as having irrigation amongst their objectives have a total storage volume of 2000 km\(^3\). The fraction of volume released annually for irrigation is thus 460/2000 = 0.23. 0.23 was thus our central estimate for \( f_{irr} \). As there was no information on the standard deviation, we assumed that the standard deviation is half of the central estimate, i.e., \( SD(f_{irr}) = 0.5 \times 0.23 = 0.115 \).

\( \epsilon_{irr} \): irrigation efficiency, i.e., how much water released from reservoirs is available to meet crop water needs “on the field”, i.e., after losses in conveyance and application. We estimate distributions of \( \epsilon_{irr} \) from data published in ref. (17). Specifically, ref. (17) list the irrigation efficiency of five different techniques (basin, furrow, basin and furrow, drip, sprinkler), and the relative share of each technique in the irrigation systems of 11 major regions (North America, Western Europe, Pacific OECD, Central and East Europe, Former Soviet Union, Planned Asia with China, South Asia, Other Pacific Asia, Middle East and North Africa, Latin America and Caribbean, Sub-Saharan Africa). Let \( t \) denote a specific irrigation technique and \( R \) a specific region. Then, \( \epsilon_{irr}(\text{basin irrigation, North America}) = 53 \% \) is the efficiency of basin irrigation in North America. The fraction of basin irrigation in North America, \( w(\text{basin irrigation, North America}) \), is 47.5 % (17). From that information, we then derive a weighted average of irrigation efficiency for each region, so that
\[
\bar{e}_{irr}(R) = \sum_{t} \frac{e_{irr}(t, R)}{w(t, R)}
\]

As well as the minimum and maximum values of irrigation efficiency, \(\min_t (\bar{e}_{irr}(R))\) and \(\max_t (\bar{e}_{irr}(R))\), (e.g., the value for the least and the most effective irrigation system in a region listed in ref. (17)). We then fit a lognormal distribution with a mean as close as possible to \(\bar{e}_{irr}(R)\) and with 99.9 % of values falling in the range of \(\min_t (\bar{e}_{irr}(R))\) and \(\max_t (\bar{e}_{irr}(R))\) (see Fig. S7 for resulting distributions and values of \(\bar{e}_{irr}(R), \min_t (\bar{e}_{irr}(R))\) and \(\max_t (\bar{e}_{irr}(R))\)). Thus, the distribution of irrigation efficiency associated to a specific dam is a function of the world region in which that dam is located, the efficiency of irrigation techniques in that region, the relative abundance of different irrigation techniques in that region and reported minimum and maximum irrigation efficiencies in that region. We selected log normal rather than normal distributions for \(\epsilon\) because of the observed skewness of min, max and average distribution values and in order to avoid negative values.

It should also be noted that part of the water that is locally lost because of low irrigation efficiency can either recharge groundwater or return to streams for downstream use. Yet, the availability and quality of those return flows might not meet requirements of downstream agriculture and are thus not considered in this study. Supplemental Table 1 lists all distribution parameters per world region (for \(e_{irr}\)) or global (for \(a\) and \(f_{irr}\)).
Supplemental Figures

Fig. S1: Location of basins highlighted in bar and boxplots in Figures 1 – 4.
Fig. S2: Future changes in storage deficits/surplus. As a result of differential growth in storage-fed irrigation and reservoir storage, storage deficits can widen (red colors) or close (blue colors). In some basins demands for stored water would outgrow increases in reservoir storage (red), but reservoir storage would still be sufficient to meet all potentials for storage-fed irrigation (low saturation colors, e.g., Mississippi). In other basins increases in reservoir storage outgrow demands for stored water (blue), but reservoir storage would still not be sufficient to meet all potentials for stored water (full saturation colors and black outline, e.g., Ganges-Brahmaputra).
Fig. S3: Regional comparison of irrigation efficiency, storage deficits, and food potential from storage-fed irrigation. Regions with great storage deficits (x-axis), have currently both the lowest irrigation efficiencies (y-axis) and the most people that could be supported from storage-fed irrigation (marker sizes). Small inset map shows the attribution of river basins to regions according to ref (17). Error bars indicate ± 1 standard deviation of irrigation efficiencies estimated from ref (17) and ± 1 standard deviation of storage deficits over 100,000 MCA runs. The analysis is shown on regional, rather than on river basin scale, to match the regional irrigation efficiency data from ref (17) (Fig. S6).
Fig. S4: Subbasins (Pfaffstetter Order 4) and main river basins. Results are derived from accumulating agrohydrologic data on a Pfaffstetter 4 level. Yet, results are reported as sum over the subbasins forming a main basin (e.g., the Amazon consists of multiple smaller subbasins), mostly easier referencing to widely used river names. All results on the subbasin level are available as supplemental data.
Fig. S5: Relative storage deficit, derived by normalizing the storage deficit/surplus by the basin area. 
a: deficit with storage-fed irrigation (SFI) on currently irrigated lands and with current dammed reservoirs. 
b: deficit with storage-fed irrigation on currently irrigated and currently rainfed land, i.e., future total, with current and future reservoirs. Grey areas indicate basins without storage-fed irrigation.
Fig. S6: a: spatial extent of different world regions from ref. (17) (note that nomenclature is directly taken from ref. (17)). Estimated weighted irrigation efficiencies by major world region (weighted average, considering for different irrigation techniques, and their spatially variable efficiency) based on data from ref. (17).
Fig. S7: Estimated distribution of irrigation efficiencies ($\epsilon_{irr}$) by major world region. In the Monte Carlo Analysis, values of $\epsilon_{irr}$ are for each dam in a specific world region according to these distributions. We fit lognormal distributions (black lines) to three points calculated from data provided in ref. (17): (1) the irrigation efficiency of the irrigation technology with the lowest efficiency (red, row 3 in Supplemental Table 1), (2) the highest irrigation efficiency (green, row 4 in Supplemental Table 1), and the weighted average (weighted by the fraction of irrigated land in each region equipped with a specific technique, row 1 in Supplemental Table 1). Values for the weighted averages also correspond to Supplemental Figure 2 b. See Supplemental Table 1 for the distribution parameters of fitted log-normal distributions (black lines).
Fig. S8: Realizing the full contribution of reservoirs to food systems will partly depend on conveyance. Examples are shown here for major subbasins of the Northern Tigris (a) and Western Ganges (b) basins (note that this matches the scale on which we conduct our agrohydrologic analysis). In many parts of these basins, the potential for future sustainably irrigated agriculture (blue) and the location of future dams (red dots) overlay closely. Future dams could contribute to existing irrigated agriculture downstream (green) and future irrigated agriculture without conveyance. Yet, in both basins there are areas where irrigation could be expanded but there are no potential upstream dams, e.g. along the Sirwan River (a) and Sone River (b). Identified future dams could contribute to irrigation in those areas only if conveyance systems are built. Note that this would require very long and probably infeasible conveyance in the case of the Tigris/Sirwan (a) and the contribution of reservoirs to irrigation in the Tigris basin would be lower than our estimate. For the Ganges/Sone, some interconnections between both rivers have been proposed. Sustainable water could thus be conveyed from planned dams through natural rivers and eventually to the lower parts of the Son River (18, 19), or water from the upper Sone River could be conveyed to downstream agriculture where it might be useful with less storage, highlighting the complexity of agricultural water storage.
Supplemental Tables

Supplemental Table 1: Statistical distribution parameters for irrigation efficiency ($\epsilon_{irr}$), storage allocation to irrigation $f_{irr}$ and the scaling factor to determine the volume of future dammed reservoirs, $a$. Those values were used to define distributions from which to draw values for each dam during the 100000 Monte Carlo runs. Note that values for $\epsilon_{irr}$ will vary for each dam as function of where it is located (see Fig. S6 a) while other parameters are global. Row ‘weighted average’ corresponds to Fig. S6 b.

| Region                        | North America | Western Europe | Pacific OECD | Central and East Europe | Former Soviet Union | Planned Asia with China | South Asia | Other Pacific Asia | Middle East and North Africa | Latin America and Caribbean | Sub-Saharan Africa | Reference |
|-------------------------------|---------------|----------------|-------------|-------------------------|--------------------|------------------------|------------|-------------------|-----------------------------|-----------------------------|---------------------|-----------|
| Weighted average              | 69.15         | 75.88          | 43.46       | 73.29                   | 66.47              | 43.70                  | 34.08      | 37.50             | 27.43                       | 42.83                       | 39.48               | Ref. (17) |
| Average                       | 69.75         | 71              | 57          | 71                      | 71                 | 63.25                  | 54.25      | 59.5              | 46.25                       | 59.5                        | 50.25               |           |
| Minimum                       | 48            | 50              | 33          | 50                      | 50                 | 40                     | 30         | 35                | 20                          | 35                          | 25                  |           |
| Maximum                       | 93            | 93              | 86          | 93                      | 93                 | 89                     | 84         | 88                | 80                          | 88                          | 82                  |           |
| $\mu$                         | 4.23          | 4.33            | 3.77        | 4.29                    | 4.19               | 3.78                   | 3.53       | 3.62              | 3.30                        | 3.75                        | 3.66                |           |
| $\sigma$                      | 0.10          | 0.08            | 0.11        | 0.09                    | 0.10               | 0.04                   | 0.05       | 0.03              | 0.13                        | 0.08                        | 0.16                |           |
| Distribution type             | log-normal    |                |             |                         |                    |                        |            |                   |                             |                             |                     |           |

| Region                        | North America | Western Europe | Pacific OECD | Central and East Europe | Former Soviet Union | Planned Asia with China | South Asia | Other Pacific Asia | Middle East and North Africa | Latin America and Caribbean | Sub-Saharan Africa | Reference |
|-------------------------------|---------------|----------------|-------------|-------------------------|--------------------|------------------------|------------|-------------------|-----------------------------|-----------------------------|---------------------|-----------|
| Allocation of storage to irrigation ($f_{irr}$) $\mu$ | 0.23          |                |             |                         |                    |                        |            |                   |                             |                             |                     | Ref. (16) |
| $\sigma$                      | 0.115         |                |             |                         |                    |                        |            |                   |                             |                             |                     |           |
| Distribution type             | normal        |                |             |                         |                    |                        |            |                   |                             |                             |                     |           |

| Region                        | North America | Western Europe | Pacific OECD | Central and East Europe | Former Soviet Union | Planned Asia with China | South Asia | Other Pacific Asia | Middle East and North Africa | Latin America and Caribbean | Sub-Saharan Africa | Reference |
|-------------------------------|---------------|----------------|-------------|-------------------------|--------------------|------------------------|------------|-------------------|-----------------------------|-----------------------------|---------------------|-----------|
| Scaling parameter for reservoir volume ($a$) $\mu$ | 3.19          |                |             |                         |                    |                        |            |                   |                             |                             |                     | Ref. (15) |
| $\sigma$                      | 8.15          |                |             |                         |                    |                        |            |                   |                             |                             |                     |           |
| Distribution type             | normal        |                |             |                         |                    |                        |            |                   |                             |                             |                     |           |
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