SPIQ-FS Dataset

Version 0

Estimation of marginal damage costs from water scarcity due to blue water withdrawal

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Summary

Marginal damage costs in international dollars (US$2020 Purchasing Power Parity) per m^3 (1000 litres) of blue water withdrawal are estimated for 164 countries. The damage costs estimate 2020 present value of present and future economic losses from water scarcity due to 1 m^3 of blue water withdrawn in 2020.

The marginal damage costs for each country are provided as random variables of loss in parametric form in Table 2 on page 35. Two parameters, mu and sigma, are estimated for a lognormal distribution of probable US$2020 PPP present values given 1 m^3 of blue water withdrawn. The samples from which the parametric form is derived and the correlation matrix for covariance of loss across countries are available in the SPIQ-FS dataset.

Use for economic loss

The objective of the SPIQ-FS dataset is to enable estimates of economic risk due to food system activities and the economic potential of food system transformation. The intended use involves aggregation across countries and quantities, for example, in global studies of dietary change or for multinational company or value chain estimates of impact.

The marginal cost estimates should not be used for local or site-specific studies.

The estimate represents aggregated economic loss to a present or future economy (e.g. reduction in Gross Domestic Product (GDP) or consumption as an income-equivalent welfare loss) and not transfers between individual economic actors or sectors (e.g. payments from households to the health sector for health costs).

The average value of probable US$2020 PPP present values given 1 m^3 of blue water withdrawn is reported in Table 2 on page 35. The average value should be used to calculate the average value of total economic losses across multiple countries and quantities since it is additive.

To calculate risk in total economic losses within a country, the distribution of probable US$2020 PPP present values given 1 m^3 of water withdrawn in Table 2 should be multiplied by a quantity of water withdrawal. This may overestimate the uncertainty in total economic losses for a large quantity of withdrawal and may underestimate the uncertainty for a small quantity of withdrawal given only the knowledge that the withdrawal occurs within the country[1].

[1] Over- or under-estimation may result since it is unclear whether $1m^3$ withdrawals by food system activities represent independent lotteries of economic loss. When aggregating to a total economic loss for n m^3 withdrawn, the sum of n random variables each with lognormal distribution given by Table 2 as a representation of the uncertainty in total economic loss should not be used without a sufficient argument for independence within the impact pathways of each unit of water withdrawn. For example, the total economic impact of CO2 emissions in 2050, treating each emission as a random draw from the distribution of economic loss for 1 metric ton of CO2 emitted and summing the random variables, will result in a gross error if economic loss is not independent between each emission due to a common component in the impact pathway (e.g. a systematic underestimate in the chemistry of radiative forcing). For water scarcity, impacts in the same catchment share common populations and uses, and income impacts across catchments in the same region are connected by price transmission. The uncertainty in economic losses from blue water withdrawal has been estimated from larger scale estimates, e.g. national rates of DALYs per person undernourished and uncertainty in national producer prices, so the overestimation is likely to be smaller than the underestimation. Uncertainty for marginal damage costs when quantities are unspecified is not fully resolved in SPIQ Version 0.

To calculate risk in total economic losses across multiple impact quantities and multiple countries, the correlation matrices in the SPIQ dataset should be used to reconstruct a joint distribution of probable US$2020 PPP present values for the impact quantities[2]. Samples from the joint distribution of marginal damages should be multiplied by their respective quantities for each country and then added. The resulting set is a sample of total economic losses. Economic risk or economic potential is generally underestimated without using joint sampling.

It is not recommended to use the average values in Table 2 separate from the uncertainty estimate.

Use for economic potential

The marginal damage costs in Table 2 and any totals for economic losses calculated using them **do not include the value (benefits) provided to society from 1m^3 of blue water withdrawn**. There is no comparison with a counterfactual to estimate the balance of value between avoided damages from water scarcity and the costs to abate blue water withdrawals. Abatement costs include the option of 'paying the cost' of losing the production value from 1m^3 of blue water withdrawn.

Reducing water use will not 'save the costs' to the global economy of amounts calculated using the values in Table 2. Damage costs should be paired with abatement costs and counterfactuals to determine the economic risk from food system activities and the economic potential in food system transformation.

The simplest use with a counterfactual is two or more scenarios which, all else being equal, have the same value from production with different quantities of blue water withdrawal. In this case, a change in overall economic value is estimated by the marginal damage costs multiplied by the change in blue water withdrawal.

Methodology and caveats

Impact pathway

Blue water deprivation at present or at a future time, which is assumed to be, through damage to the water resource from blue water withdrawal, the effective reduction of the total amount of blue water available for economic activity, is taken from a spatial dataset from literature.

Deprived water is assumed to concentrate in reduced agricultural use and crop production. Reduced crop production introduces malnutrition or income losses in households not at risk of malnutrition. Disease or death from malnutrition reduces gross productivity.

Reduction in environmental flows and effects on ecosystem services were not included due to lack of quantitative estimates of water as a productivity factor for ecosystem services.

Reduced water for drinking and sanitation were not included due to lack of quantitative estimates of the attribution of deprived units of water to human disease from reduced water intake and lack of

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[2] Covariance in economic losses due to joint emission or production of impact quantities from food system activities, for example 1 m^3 of water withdrawn in country i and 1 metric ton of CO2 emitted in country j, is estimated in the document "SPIQ-FS Version 0: double counting and estimation of correlations between impact quantities". The parametric form given in Table 2 represents what is called the marginal distribution of a joint distribution across countries and quantities of marginal damages for the impact quantities associated to food system activities. Determination of the correlations considers spatial and temporal coincidence of impact. All SPIQ-FS Version 0 damages are for impact quantities produced in 2020. A later version may consider joint distribution across countries and quantities and years of emission/production.

sanitation. Global datasets were not available for estimates of drinking water costs, e.g. loss of productivity from additional walking distance to freshwater sources.

Later versions of SPIQ-FS will consider effects on ecosystem services and drinking water and sanitisation.

Calculation and uncertainty

Calculating economic losses of malnutrition from reduced food production is based on an established Life Cycle Impact Analysis (LCIA) methodology. The Food and Agriculture Organisation of the UN (FAO) measure of undernourishment is used as the proxy for number of people in malnutrition and economic loss is measured by productivity loss from Disability-Adjusted Life Years (DALYs) of energy-protein malnutrition as defined by World Health Organisation (WHO).

Value of crop losses are estimated using a spatially explicit dataset from literature of contribution of water to major crop production. The value of crops is based on FAO producer (farm-gate) prices.

Large uncertainty exists in the water deprivation factor, including uncertainty which uses will be deprived and when. The spatial dataset for deprivation had no temporal aspect, so uncertain time of deprivation was modelled. Uncertainty in models for the number of undernourished people due to reduced food production, and the rate of DALYs in an undernourished population, was accounted for. Historical variation in producer prices, and correlation amongst countries, was incorporated in income loss estimates.

The variation between countries is large, from US$2020 PPP 200-300 per megalitre of blue water withdrawal in wealthy middle east countries and the east Mediterranean to US$2020 PPP <1 per megalitre in water abundant countries and/or countries with low use of irrigation. There are mainly four reasons for these variations:

1) Variation in water stress (a component of the water deprivation factor and in the temporal parameters used for discounting) is the dominant factor.
2) Countries have differing productivity of blue water as a component of farm-gate value of crops.
3) Difference in productivity loss is the third factor in country variation. Productivity losses from DALYs are estimated by labour productivity statistics (International Labour Organisation (ILO)) and averaged across human development (Human Development Index (HDI)) tiers.
4) Lastly, the uncertainty of projected GDP growth introduces variation between countries.

Caveats in the estimate of water deprivation include a lack of transboundary effects, the averaging of value of crop losses across catchments, and ambiguity in the LCIA model of attribution of deprived water to population undernourishment. The complexity of connecting by-products of food system activities to accumulated natural and human change, and then economic consequences, is a primary motivation to model uncertainty alongside estimates. Potential improvements will be afforded by a greater emphasis on spatially explicit modelling in SPIQ-FS Version 1.

Damage costs in the SPIQ-FS dataset are not valuable for direct comparison of countries. The costs represent primarily the externalised costs of blue water use for market corrections in the economies where the costs are borne. Low-income countries are doubly discounted from a higher expected growth rate in the future, current lower use of irrigation, and lower values of labour productivity losses.

Global perspective

For perspective, FAO estimates of blue water withdrawal for agriculture across 164 countries are paired with the marginal damage costs (Section 2.6 from page 26 and Section 2.11.2 from page 44). Estimated global costs of present blue water withdrawal for agriculture are over US$2020 PPP 110 billion, with a greater than 5% chance that costs are over US$2020 PPP 150 billion. India represents over a quarter of the total damage costs with an expected loss of US$2020 PPP 34 billion. How much of this estimated economic loss can be recovered from transforming food systems and agricultural production is unclear without global modelling studies of blue water abatement.

Annex A

Contents

2 Water Use

2.1 Quantities associated to impact

Agriculture is responsible for 70% of global freshwater withdrawals (varying geographically from 12% in South and Central America to 53% in North America and 81% in Asia and Africa, FAO global information system on water resources and agricultural water management (AQUASTAT)). Agriculture consumes 85% of the water that is withdrawn and not returned to the same catchment [1].

Increasing water scarcity [2, 3] and decreasing water quality [4] are the two main causes of impacts associated to food system water use.

Marginal costing below focusses on the impacts of water scarcity and use the unit of m^3 yr^{-1} of blue water withdrawn from surface and groundwater sources.

Impacts of water quality in terms of nutrients are included in other marginal costs:

- Nitrogen pollution run-off and ground water leaching.
- Phosphorous pollution run-off.

Water quality factors not included:

- Soil erosion (sediment).
- Chemical pollutants from industrial food processing [5].
- Biochemical contaminants, including antibiotic residues [6].
- Downstream effects of the use of untreated wastewater in agriculture [7].

2.2 Damage components

2.2.1 Agricultural use of water

Agriculture activities consume green water (direct precipitation) and blue water (freshwater withdrawn from lakes, dams, rivers, and aquifers). Blue water withdrawals are costed as a proxy for blue water consumption, but green water consumption is not costed directly.

Crops, and livestock production on grasslands, consumes more green water than blue water. The majority of cropland is solely rainfed (green water), irrigated cropland globally uses ~600 km3 yr-1 of blue water and 325 km3 yr-1 of green water, and non-irrigated cropland globally ~7000 km3 yr-1 of green water [8]. Green water cropland consumption is estimated at ~18% of green water flow to ecosystems [8].

Crop production, through the market price of cereals as input for feed, reflects most of the value of water to livestock production on an aggregated basis. The bulk of livestock water use is in feed, not direct drinking water [9]. In certain grazing locations and livestock systems, drinking water will be a primary water input. Food system effects on green water availability rest on atmospheric and hydrological effects (i.e. the impacts of which should be attributed to GreenHouse Gas (GHG) emissions and land-use change, not blue water withdrawal from freshwater sources [3]).

Blue water withdrawal overestimates blue water consumption. However, agricultural uses are highly consumptive compared to other sectors, and a lack of data on water consumption, has led to water withdrawal as the metric used in most analyses and costings [8].

2.2.2 Overuse leading to scarcity and impacts

Water withdrawal can lead to water scarcity and water deprivation. Water deprivation is a reduction in the total water utilised in the water resource for present or future uses including environmental flows for ecosystems. The reduction in water utilised has human, ecosystem, and agricultural impacts [10]:

- Costs to human populations from reduced availability of water for sanitation and drinking [11].
- Losses to (crop) production occurs through change in water available for irrigation [12, 13].
- Losses from impaired ecosystem services due to reduced environmental flows.

Mining and energy production, besides agriculture, households, and ecosystems, are the other major and spatially heterogeneous blue water users.

2.3 Existing estimates of marginal costs

Water scarcity impacts have local marginal damages, that can vary even within watersheds [14]. Mitigation measures are local as well: a different measure can be cheaper to abate the same amount of withdrawal of the same agricultural activity in different catchments [10]. Therefore marginal social costs are challenging to calculate.

The estimates that exist are based on water deprivation – a reduction in available water in the present or a future time from water withdrawal in the present, and they concentrate on losses from crop production (**malnutrition** or **income loss**). Sophisticated but exploratory studies of future trajectories of water deprivation have been conducted [10]. Incorporating these studies is future work. No simple estimates on a catchment or country basis could be found for the trajectory of water deprivation from a water withdrawal in the present. We therefore use present estimates of crop value and malnutrition for a unit of blue water deprived in the present as a proxy for a future blue water deprived and discount the final cost using an uncertainty distribution over time of the deprivation caused by a withdrawal now.

Ecosystem service losses from water scarcity outside of food production do not appear to have been systematically costed. Damages from scarcity through impacting household sanitation and drinking also do not appear to have been systematically costed. Improved costings would add these components – under the provision that double counting between social damages of poverty and sanitation outcomes is examined, and the complex interaction required to assess ecosystem impairment given water scarcity, excess nutrients (Nr emissions) and land use changes is accounted for.

2.3.1 Malnutrition from crop loss

The reference [11] estimates population malnutrition impacts from deprived units of water. A chain of components is multiplied together to form the estimate (equation (1) below). The term EF_i (ppl / m^3 deprived) is the rate of people undernourished due to the deprived water to agriculture in country i. The term DF_i (DALY / ppl) is the rate of DALYs (WHO 2019, energy-protein malnutrition) against the number of people undernourished in country i. The term CF_i is the economic cost to country i of a DALY lost to malnutrition in international dollars (US$2020 PPP / DALY). Finally, the term WDF_i (m^3 deprived / m^3 withdrawn) calculated in [11] is the deprivation factor, it is meant to estimate what is the rate of deprived water to agriculture against blue water withdrawal from surface or groundwater sources (not desalination). Note that a unit of blue water of withdrawal does not cause a deprived unit of water unless there is water scarcity (insufficient blue water for the current level of crop production). The term WDF_i is a function of total blue water withdrawals. The marginal damage cost (US$2020 PPP / m^3 withdrawn) of malnutrition in country i of a unit of blue water withdrawal from surface or groundwater sources is:

$$MDC_{mal,i} = CF_i \cdot DF_i \cdot EF_i \cdot WDF_i. \quad (1)$$

For 158 countries with available data, the calculation of the terms and uncertainty estimates are in the section on estimation and uncertainty below.

The method of [11] calculates no prevalence of malnutrition impacts in countries with HDI > 0.89. To separate out conflation (double counting) of malnutrition and income loss effects for agricultural workers, prevalence of malnutrition for agriculture workers is used. Those households with malnutrition suffer the damage cost of malnutrition, and those without suffer the crop loss effect on income from [13]. This underestimates the combined malnutrition and income loss effects. Income loss from crop loss is the impact for countries with HDI > 0.89.

2.3.2 Income from crop production

The present value of a unit of blue water (irrigation) to crop production has been determined globally using a mechanistic biophysical model in [13]. The valuation examined 16 major crops at the global scale on a 10-km grid using a productivity function approach. It used 2019 farm gate market prices of the current crops produced on the land cell (FAOSTAT). FAOSTAT producer prices converts local currencies into internationals dollars (US$ PPP). Production is assumed to not be limited by other inputs, including nitrogen (N) and phosphorous (P).

Deprived units of blue water across different catchments results in reduced supply of crops. The marginal damage costs from [13] assume negligible costs for provision of irrigated water. Effects on other economic activity from reduced agricultural production is not included. Assuming the same demand, then prices would increase. The change in prices due to simultaneous scarcity occurring in other basins may imply that the economic return from the remaining production of crops outweighs the loss of production at previous prices [10] – this kind of correction needs to be accounted for in more sophisticated estimates, with caveats on the engagement of crop producers in various countries with international trade.

There is no dependence of the marginal damage cost on the total amount of withdrawals in the same or other basins using the calculation of [13], outside of the present value and distribution of crops influenced by present hydrological availability and total withdrawals. Present dependence is partially captured in the correlation structure of joint uncertainty in producer prices modelled below. The correlation is based on historical data, not a future with increased environmental change. The distributional effects of human cost from lost crop production, or equivalently, higher prices, is partially captured by a malnutrition component of the impact assessment of [11].

Let $VF_{inc,i}$ (US$2020 PPP / m^3 deprived) be the average value loss to agriculture from crop loss in country i due to a deprived unit of water calculated from [13]. Using the water deprivation estimate WDF_i, then a marginal damage cost to agricultural income from crop loss in country i is

$$MDC_{inc,i} = VF_i \cdot WDF_i. \quad (2)$$

There is no temporal aspect to WDF_i from [11] in either (1) or (2). The distribution in time of the losses from water deprivation materialising from a water withdrawal in the present is uncertain. No simple estimates on a catchment or country basis could be found for the trajectory of water deprivation from water scarcity. A representation of this uncertainty is given below by discounting the monetary amount in (1) and (2) by a distribution of discount rates.

2.3.3 Marginal damage cost for water withdrawal

A national level marginal damage cost (US$2020 PPP / m^3 withdrawn) from a unit of blue water withdrawal somewhere within country i is

$$MDC_{water,i} = \rho_i \cdot \left(MDC_{mal,i} + (1-\alpha_i) \cdot MDC_{inc,i}\right) \tag{3}$$

where α_i is the prevalence of malnutrition in agricultural workers in country i to avoid double counting income and malnutrition effects, and ρ_i is a discounting term for uncertainty in when the cost is incurred.

The equation (3) is formalised and calculated with uncertainty using data from [11] and [13] below. Estimates using (3) do not include the income effects on farming households with malnutrition outside of the role of income in malnutrition. They do not consider that households without malnutrition are likely the households where a greater proportion of crops are grown. The estimate (3) is at a country level and takes the average marginal damage cost for crop loss in that country. Therefore, it does not account for greater volumes of water withdrawn within catchments with higher value agriculture. A more accurate estimate afforded by the resolution in [13] is to average marginal damages losses from crop losses across catchments, if the quantity of total water withdrawals per catchment are used as the quantities of impact. Other considerations from lack of temporal resolution in impacts are discussed below.

Estimates for the uncertainty in $MDC_{mal,i}$, α_i, ρ_i, and $MDC_{inc,i}$ are discussed below.

2.4 Formalising damage costs

Estimating the partial rate of change of damage costs D given blue water withdrawal w_j at spatial location j, when the damage cost has the components of: S_k reduced availability of water for sanitation and drinking at time t in a water catchment k; malnutrition M_i and losses to income I_i at time t in a country i; and reduced environmental flows damaging ecosystem services E_k at time t in a water catchment, can be formalised by,

$$\frac{\partial D}{\partial w_j} = \int_0^\tau \rho(t) \left(\sum_i \frac{\partial D}{\partial M_i}(t) \frac{\partial M_i}{\partial w_j}(t) + \frac{\partial D}{\partial I_i}(t) \frac{\partial I_i}{\partial w_j}(t) + \sum_k \frac{\partial D}{\partial E_k}(t) \frac{\partial E_k}{\partial w_j}(t) + \frac{\partial D}{\partial S_k}(t) \frac{\partial S_k}{\partial w_j}(t) \right) dt$$

where $\rho(t)$ is a discounting function equating the value loss of future impacts in the time period $[0, \tau]$ to present value $t = 0$. Without loss, the sum is over all countries and catchments. Recall that countries (and regions) represent a hierarchal cover of the spatial locations j. The notation i_j represent the catchment, country, or region i such that $j \subset i$. The simplifications in equation (3) from available spatially explicit global estimates are:

$\frac{\partial D}{\partial M_i}(t) = 1$ - damage cost is linear in costs of malnutrition and constant in time

$\frac{\partial M_i}{\partial w_j}(t) = MDC_{mal,i} \cdot \delta_{i,i_j}$ - no transboundary malnutrition effects of water withdrawal, malnutrition costs in country of withdrawal constant in time and calculated from [11]

$\frac{\partial D}{\partial I_i}(t) = (1-\alpha_i)$ - remove double counting between agriculture income and malnutrition effects, constant in time

$\frac{\partial I_i}{\partial w_j}(t) = MDC_{inc,j} \cdot \delta_{i,i_j}$ - no transboundary income effects of water withdrawal, income losses to producers in country of withdrawal from water withdrawal at location j constant in time and calculated from [13]

$\frac{\partial D}{\partial E_k}(t) = 0$ - no ecosystem services losses (excluding food provision in agri-ecosystems) in any catchment k from water withdrawal at location j

$\frac{\partial D}{\partial S_k}(t) = 0$ - no costs from lost access to blue water for drinking and sanitation in any catchment k from water withdrawal at location j.

We have not specified the resolution of the catchment partition of locations, which are not subordinate to the partition of locations by country. If the spatial locations of water withdrawal are the countries themselves (the quantity is a unit of withdrawal somewhere within the country), then in this case $MDC_{inc,i}$ is the average marginal damage cost to income from crop loss calculated from [13] as described. Then we obtain (3): $\frac{\partial D}{\partial w_i} = MDC_{water,i}$.

To not be overly technical, we have not specified functional dependence of the vectors of intermediate costs,

$$\boldsymbol{M} = \{\boldsymbol{M_i}\}_{\boldsymbol{i \in countries}}, \boldsymbol{I} = \{I_i\}_{\boldsymbol{i \in countries}}, \boldsymbol{E} = \{E_k\}_{k \in catchments}, \boldsymbol{S} = \{S_k\}_{k \in catchments}$$

on the lists of quantities, including the vectors of quantities,

$$\boldsymbol{c} = \{c_m\}_{m \in CO2, CH4, N2O\ emissions}, \boldsymbol{w} = \{w_j\}_{j \in water\ withdrawal\ locations},$$
$$\boldsymbol{n} = \{n_m\}_{m \in Nr\ emission\ locations}, \boldsymbol{l} = \{l_r\}_{r \in land\ use\ change\ locations}.$$

Of particular focus are ecosystem services losses in a catchment, where the functional dependence of ecosystem services on water available, nutrients, and land use implies a non-constant term,

$$\frac{\partial E_k}{\partial w_j}(t, \boldsymbol{c}, \boldsymbol{w}, \boldsymbol{n}, \boldsymbol{l}).$$

Costing the attribution of water withdrawal to ecosystem services damage costs without a functional relationship between the other critical quantities will result in an ambiguous result. It is unclear without estimation whether simpler approximations underestimate or overestimate damage costs to a significant degree. A first order approximation to $\frac{\partial E_k}{\partial w_j}$ requires at least knowledge of the second order rates at present or specified values $t_0, \boldsymbol{c_0}, \boldsymbol{w_0}, \boldsymbol{n_0}, \boldsymbol{l_0}$,

$$\frac{\partial^2 E_k}{\partial t \partial w_j}(t_0, \boldsymbol{c_0}, \boldsymbol{w_0}, \boldsymbol{n_0}, \boldsymbol{l_0}), \frac{\partial^2 E_k}{\partial c_m \partial w_j}(t_0, \boldsymbol{c_0}, \boldsymbol{w_0}, \boldsymbol{n_0}, \boldsymbol{l_0}), \frac{\partial^2 E_k}{\partial w_{j_1} \partial w_{j_2}}(t_0, \boldsymbol{c_0}, \boldsymbol{w_0}, \boldsymbol{n_0}, \boldsymbol{l_0}),$$
$$\frac{\partial^2 E_k}{\partial w_j \partial n_m}(t_0, \boldsymbol{c_0}, \boldsymbol{w_0}, \boldsymbol{n_0}, \boldsymbol{l_0}), \frac{\partial^2 E_k}{\partial w_j \partial l_r}(t_0, \boldsymbol{c_0}, \boldsymbol{w_0}, \boldsymbol{n_0}, \boldsymbol{l_0}).$$

Global simplified joint models of the carbon, nitrogen, biosphere, and water cycles would be required to approximate the second order terms. In the absence of a joint model the inclusion of correlations, Section 2.7, reflects some of the effect of the second order terms for joint interaction between water scarcity, climate impacts, nitrogen pollution and land-use change.

The formalisation above does not separate out blue water withdrawal from surface and recharging groundwater blue water sources, against non-recharging (or slowly recharging) groundwater sources. The two have differences in their impact pathways.

2.4.1 Temporal aspects

The components of the marginal water damage costing have discounting effects from the fact that water withdrawal is assumed to create water deprivation, and hence losses, at present or future times. Calculating the time at which water withdrawal now will cause deprivation, and losses at that time, requires future scenarios of water use and socio-economic factors and that the quantity of blue water withdrawal be separated into withdrawal from renewing and non-renewing sources. The temporal component and the distinction in sources in not included in the method of [11] (Figure 1).

Evaluating the marginal water damage cost for a future time can be estimated through time dependence of relative components [15] [10]:

- change in water deprivation at the future time (considering variation in the future from climate factors such as precipitation and temperature) as a function between future water availability and water uses for industry drinking and sanitation, agriculture, and the environment.
- projected changes in the value and distribution of crops at the future time.
- projected changes in vulnerability to malnutrition at the future time, which can be partly reflected through improvements in income and HDI.

If the marginal cost of water includes sanitation and ecosystem impacts, the time dependence of these factors include:

- future impairment of ecosystem services due non-water factors
- future changes in downstream sanitation exposure of human settlements.

Reduced blue water availability from green water consumption of agriculture in the present, may cause future scarcity in combination with present blue water withdrawals from non-renewing groundwater. However, green water consumption is a different economic quantity than blue water withdrawal and costing green water consumption requires more distinction in the quantities associated to impact and the impact pathways (Figure 1).

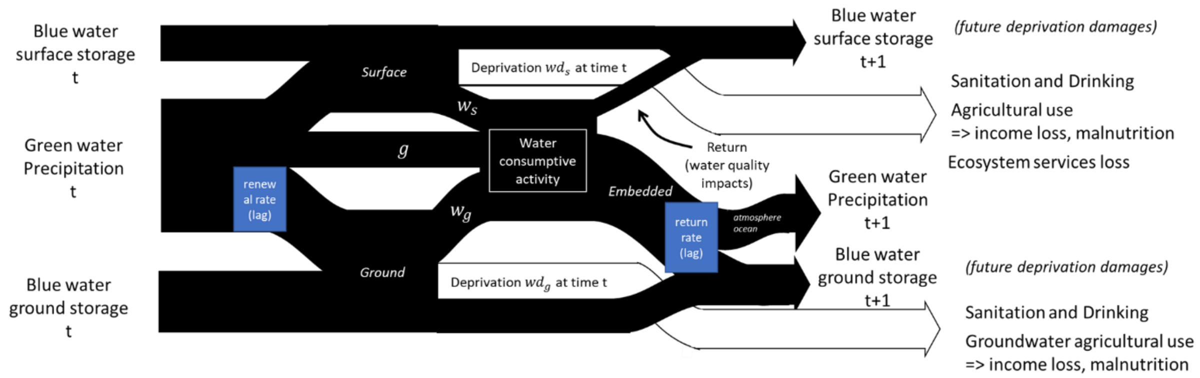

Figure 1: Schematic of further distinction in impact pathway for blue water withdrawal between surface (w_b) and ground water (w_g) sources. Green water consumption (g) in agricultural may increase deprivation, and hence increase water scarcity impacts, by reducing available surface and ground water. Lags in renewal and return rates to ground water sources

may increase future deprivation damages from ground water withdrawal compared to surface withdrawal. Water quality impacts sources from return of non-consumed withdrawn water not shown.

A potential simple method to include green water consumption is in the term WDF_i, since total water availability is reduced. The effect on groundwater withdrawal would be more complicated because of lag (determined by the groundwater recharge rate). WDF_i could be improved in its contextual and temporal representation. Models such as WaterGAP2 can provide estimates of green water run-off, ground water recharge, surface flows, and storage [16].

Damage from future water deprivation due to water consumption in the present requires the recalculation of (3) under future conditions as described, and then discounting the future costs to present. The uncertainty in social and environmental conditions can create large uncertainty in the future economic impacts [10].

2.5 Calculation and uncertainty

The components of (3) have variation across countries, but also potentially uncertainty in the amount of malnutrition and income loss caused, and their costs.

2.5.1 Water deprivation component

The WDF (water deprivation factor – the portion of blue water withdrawn that results in blue water deprived to agricultural user of the water resource) calculated in [11] is spatially explicit, up to country level and where data is available up to major watershed level (watersheds in the WaterGAP2 model [16]). WaterGAP2 was used to estimate the WaTer Availability (WTA_k) in a watershed k as the ratio of the total annual withdrawal by agricultural, industry and household users from total annual hydrological availability. WTA introduces a dependence on total withdrawals in a catchment. To capture the coupling between seasonal changes in water use by the sectors with variation in hydrological availability, WTA was multiplied by factor based on the standard deviation in monthly precipitation over the watershed (or its root in water catchments with significant blue water storage). To renormalize this to a value between 0 and 1, a logistic transform was used. This procedure, from [11], derived a number Water Stress Index (WSI_k) between 0 and 1 that is meant to represent: if m^3 blue water is withdrawn from blue water sources in catchment k, then WSI_k m^3 of blue water is deprived (in the present or at some later time) from an agricultural, household, or industry user of blue water from catchment k. There is no temporal representation in [11]. Multiplying WSI_k by the proportion of agricultural use versus total use (in the present) is the value WDF_k. [11] derived water use from the spatially explicit calculation in [15].

Deprived m^3 water in a catchment is derived in [11] from water scarcity and not estimated nor modelled based on observed quantities of deprivation, making it difficult to estimate uncertainty and understand the variance in Prevalence of Undernourishment (PoU) caused by deprived m^3 water in a catchment. Potential uncertainty in deprived water to an agricultural user can come from (a) proportion of deprived use amongst the three users (households, agriculture and industry), (b) spatial variation in withdrawal, and (c) temporal variation in withdrawal, total use, and total hydrological availability:

a) The proportion of agricultural use versus total use is taken as the probability that the deprived user will be an agricultural user. Fluctuation in agricultural use within a catchment over time and measurement of agricultural use creates uncertainty in WDF_k. Markets or regulations in the catchment prioritising industry and household use as more valuable could change the likelihood that the user is agricultural. Industry sectors generally outcompete agriculture for purchasing local water rights [13, 17]. The present proportion of agricultural use to other is a fair reflection of present priorities, so no uncertainty is assumed for present impacts when the water withdrawal w is small relative to the total withdrawal in the water catchment. Impacts if the water were deprived in the present are used as a proxy for future impacts in our simple estimate. If w is comparative to total withdrawal, then the dependency of WSI_k on w could change priorities of use, increasing the proportion of deprivation for agricultural users.

b) It is assumed that the water deprivation from the water withdrawal occurs randomly anywhere in the catchment in [11], and that all agricultural users are homogenous (identical) and identically distributed in the catchment. Spatial heterogeneity in agricultural use and deprivation would introduce uncertainty in the loss of crop production. As w increases then water deprivation increases an increasing number of agricultural users become deprived and the crop loss would tend toward the average of users. This uncertainty would decrease, but the uncertainty in (a) would increase.

c) It is uncertain when in the year the withdrawal occurs and how that matches with interannual variability, inter-monthly use and availability (including storage), and damage to water resources. Multiplying a random variable distribution by relative amount of withdrawal over months of the year against interannual variability and inter-monthly use and availability (including storage) and vulnerability of the water resource would better reflect this uncertainty than multiplying WTA by the standard deviation in precipitation over the watershed. Temporal variation of deprivation over years would require the modelling discussed in Section 2.4.1 above. Uncertainty in the future year of deprivation is modelled by uncertainty in the discount factor ρ_i.

Since the uncertainties in (b) and (a) are related as w increases, independence of their effects is not clear, and it is not a simple conclusion that WDF_k as derived above is the average amount deprived to an agricultural user in the catchment. Data was not available to model the uncertainties explicitly and include the dependence on w (the quantity of blue water withdrawal) in WDF_k.

For use in equation (1) (the use of WDF_k in equation (2) is described below) the water withdrawal quantity is expressed as water withdrawal in a country i. It is uncertain which catchment withdrawal is from and hence which water resources may be damaged by withdrawal. Averaging across the catchments assumes the water withdrawal is taken in equal proportions from each catchment. Unless it is known which catchment the water withdrawal is from (in which case a study should use WDF_k), this introduces uncertainty in the factor WDF_i used in equation (1). Because of the interaction between (a) and (b) as the size w increases, this uncertainty should be adjusted to the study. Lifecycle analysis studies using the marginal costings of water where catchment of withdrawal is not known should model this uncertainty as an approximately normal distribution (distribution of average from w experiments of a unit of blue water withdrawn in randomly chosen Bernoulli trials with outcomes $\{0, WDF_k\}$ and probability $\gamma_{i,k}$, where $\gamma_{i,k}$ is the proportion of agriculture users of catchment k in country i).

In equation (2) we derive the value for WDF_i from WSI_i in the dataset of [11] and the proportion of agricultural use of surface and groundwater withdrawals for country i from AQUSTAT[3]. Even though a single value is used for WDF_I it is a random variable, the distribution of which is yet to be

[3] An alternative to [9] with a spatially explicit data set is called water depletion http://www.earthstat.org/water-depletion-watergap3-basins/

determined and would depend on the context and magnitude of the withdrawal. This uncertainty is reflected partly in the lognormal fit of (1) and (2) as products of random variables in Section 2.6.

For greater spatial resolution the reference [12] has an alternative 30 x 30 arcmin grid of irrigated water use (WC_IRR,CURR) and calculates calorie reduction from deprived irrigated water. Calorie intake/capita against ppl malnutrition (or direct to DALYs) could be an alternative model for the following.

2.5.2 Malnutrition damage costs from water deprivation

The term DF_i from [11] can be written as the partial rate of change of DALYs per annum per capita (DALY yr^{-1} $capita^{-1}$), which we obtained from (WHO 2019, energy-protein malnutrition), against the prevalence of undernourishment PoU_i for country i (ppl yr^{-1} $capita^{-1}$). There are enough data points for countries (148) to perform an implied quadratic surface fit from reference [11] of DALY yr^{-1} $capita^{-1}$ as a function of PoU and HDI ($0 \leq PoU \leq 1, 0 \leq HDI \leq 0.89$), see Figure 2,

$$\text{DALY/yr/capita}(PoU, HDI) = \beta_1 + \beta_2 \cdot PoU + \beta_3 \cdot HDI + \beta_4 \cdot PoU \cdot HDI + \beta_5 \cdot HDI^2 .$$

The r value of the Maximum Likelihood Estimate (MLE) fit of the surface when HDI <= 0.89 is r=0.83. HDI is a primary explanatory factor for when undernutrition in a population translates into preventable disease and death [18]. Linear interpolation between 0.89 < HDI <=1 can be used to extend the surface. However, since PoU is very low when HDI > 0.89, we take DF_i= 0 for HDI >=0.89 following [11] (the reference [11] uses data from 2009, we used data from 2019). Data on Mali and North Korea were excluded as outliers from the fit. When HDI < 0.89, then an estimate for DF_i is the partial derivative of the fitted surface

$$DF_i = \frac{\partial \text{ DALY/yr/capita}}{\partial PoU}(PoU_i, HDI_i) = \widehat{\beta_2} + \widehat{\beta_4} \cdot HDI_i,$$

where the values $\widehat{\beta_2}$ and $\widehat{\beta_4}$ are the MLE parameters. The partial derivative can be seen as the slope of the lines in the DALY/yr/capita and PoU plane in the second panel of Figure 2. The dependence on HDI changes the slope. Figure 2 also shows that linear regression of DALY/yr/capita against PoU (as done in [11]) without factoring over HDI overestimates by an order greater than 2 the value of the partial derivative DF_i.

Uncertainty in the value of DF_i derived from model fitting was not examined in [11]. For an uncertainty estimate of DF_i when HDI < 0.89 we used a Bayesian regression on the parameters of the surface fit. Residuals on the MLE surface fit were fitted to different distributions for HDI < 0.625, 0.625 <= HDI <0.75 and HDI>=0.75 due to heteroscedasticity in the residuals in HDI as seen in Figure 11 (larger errors as HDI decreases in the left panel). Three distributions of residuals for the different intervals of HDI (right panel of Figure 11) were used to characterise the shape of likelihood functions for updating priors on $[-1,1]^5$ for the parameters

$$\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$$

in the quadratic surface fit ($0 \leq POU \leq 1, 0 \leq HDI \leq 0.89$). Priors were uniform but constrained to reflect the beliefs: $\beta_2 \geq 0$ (the belief that increase in PoU is certain to increase DALYs from malnutrition at all levels of HDI), $\beta_3 \leq 0$ (the belief that increase in HDI is certain to decrease DALYs from malnutrition at all levels of PoU), $\beta_4 \leq 0$ (the belief that increase in HDI and decrease in PoU simultaneously will decrease DALYs), $\beta_5 \geq 0$ (the belief that an accelerating rate of DALYs from malnutrition as HDI decreases is certain).

Annex A

This approach may be summarised as β is a random variable representing uncertainty in the value of DF_i derived from a model of the observed (DALY yr^{-1} $capita^{-1}$ malnutrition, PoU, HDI) triples in 2019. A joint distribution on β (derived from the Bayesian regression method described) represents the probability that the observed values of (DALY yr^{-1} $capita^{-1}$ malnutrition, PoU, HDI) could, up to random errors, have resulted from the relationships between DALY yr^{-1} $capita^{-1}$ malnutrition, PoU, and HDI described in the model β (instead of the MLE model). The variables $(\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$ are strongly correlated in fitting a quadratic model (there is a lot of uncertainty with the data presented whether, at lower levels of HDI and higher levels of PoU, the degree to which HDI or PoU is the primary factor in malnutrition resulting in DALYs), therefore the joint distribution on the parameter space should be sampled and not the marginals in β_2 and β_4 estimated separately.

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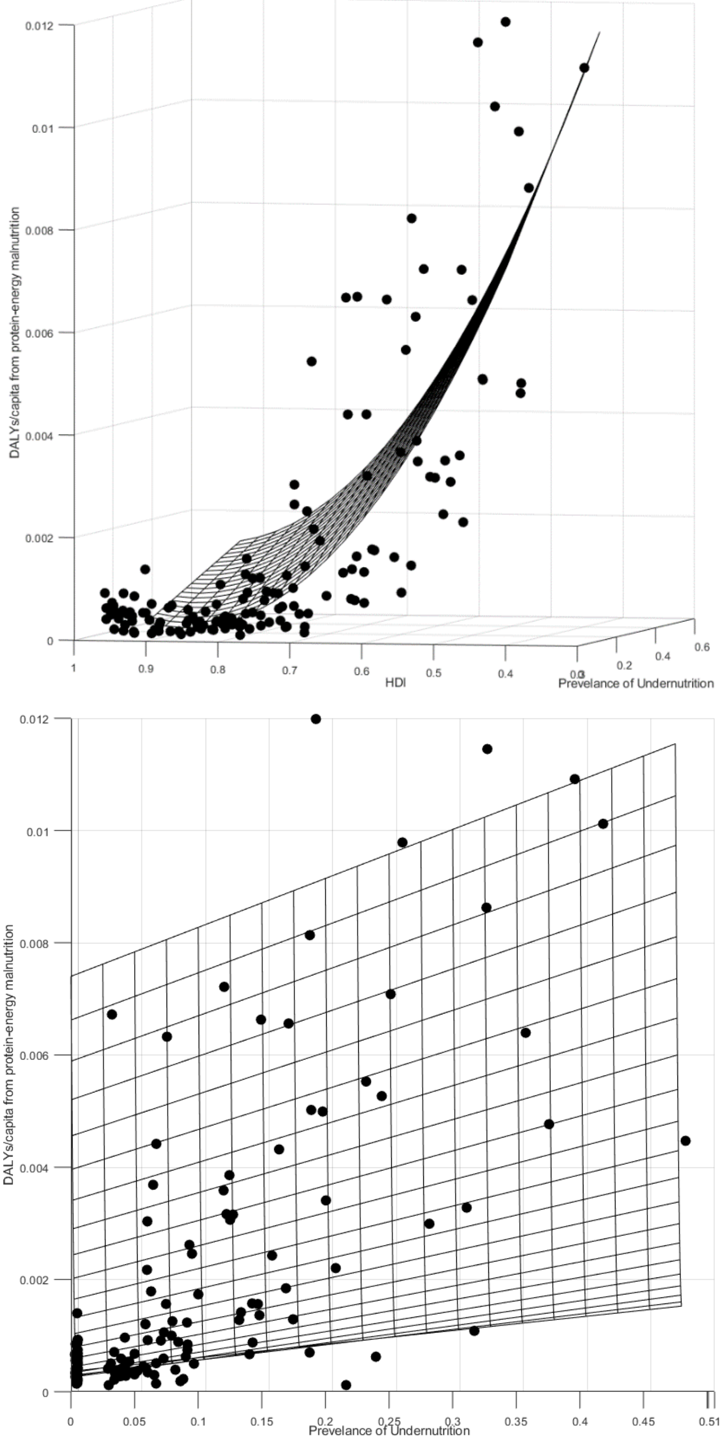

Figure 2: Fit of quadratic surface between DALY/yr/capita, prevalence of undernutrition PoU, and human development index HDI, with 2019 data from 148 countries.

1000 samples of β_2 and β_4 were drawn from a joint sample of β, providing 1000 samples for

$$DF_i = \beta_2 + \beta_4 \cdot HDI_i.$$

The Bayesian estimates compared to the MLE values of DF_i for representative countries in HDI bands are shown in Figure 3, Figure 4 and Figure 5. At higher HDI the Bayesian estimate of the attribution of DALYs to percentage of the population suffering malnutrition underestimates the Ordinary Least Squares (OLS) MLE estimates (the surface fit in Figure 2). The increasing influence of higher HDI on reducing the chance of DALYs in the presence of malnutrition in the data is reflected in the Bayesian estimates by local quadratic curve fitting in the HDI bands in Figure 11 and modelling positive skew in residuals as HDI increased, both of which the OLS MLE fit does not account for. The sharp distinction between residuals for HDI less than or greater than 0.75 (left panel of Figure 11) was smoothed by interpolating over the band 0.7 < HDI < 0.8.

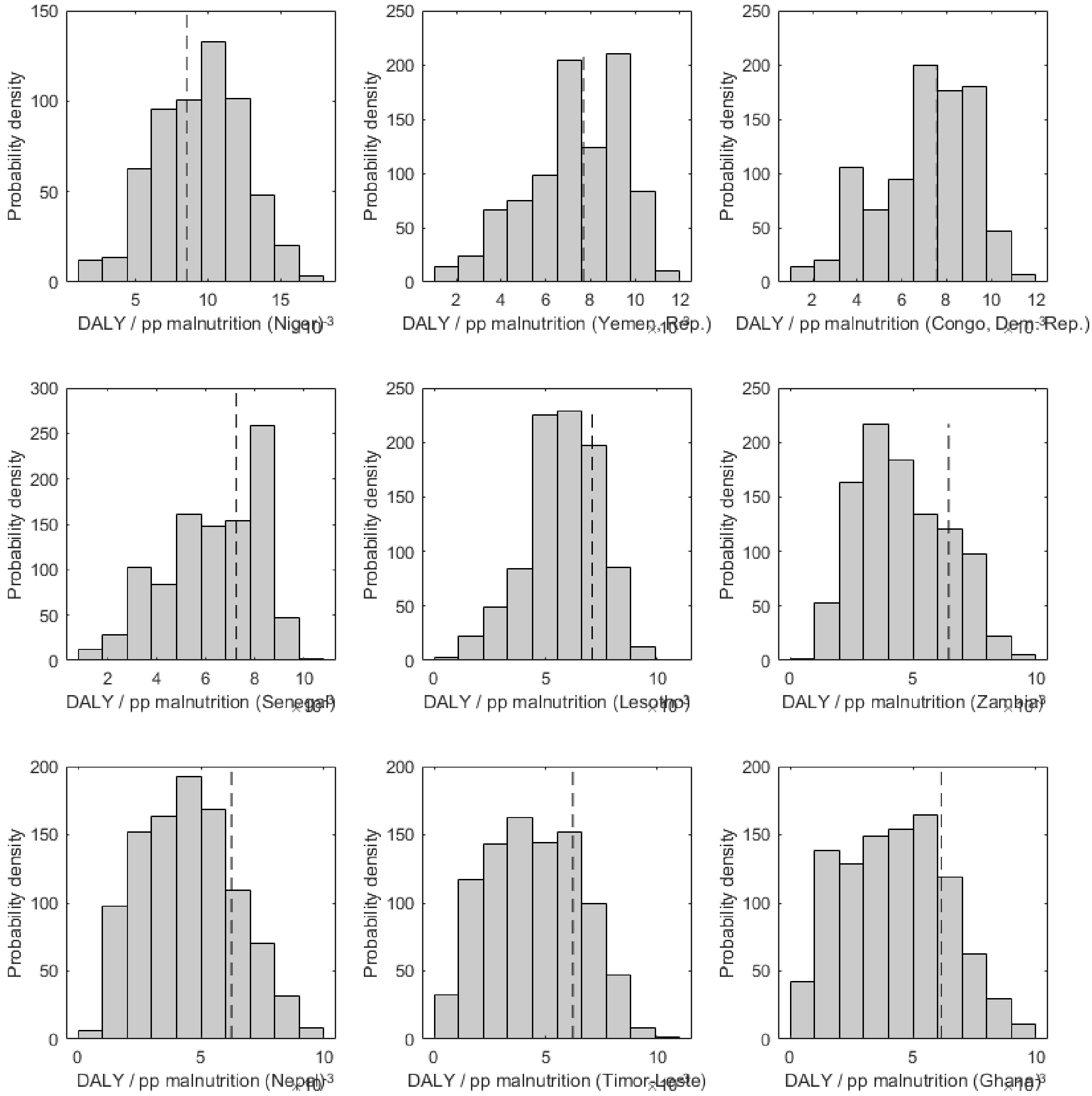

Figure 3: the factor DF_i in the estimation of the costs of malnutrition due to water deprivation in 9 example countries HDI < 0.625, following [10]. Uncertainty and adjustment in the OLS MLE values (dashed lines) comes from uncertainty in model fitting and heteroscedasticity in HDI of residuals (Figure 11). HDI ranges from lowest HDI in the top panels to those countries with HDI closest to 0.625 in the bottom panels. Heteroscedasticity in HDI for residuals (using is a linear trend in HDI for variance of residuals within the region HDI < 0.625) can be observed in the shift of central mass above OLS MLE to below OLS MLE values as HDI increases (from low HDI in top panels to higher HDI in lower panels). From the fit, the mean rate in Niger (HDI 0.394), for example, is 10 DALY for every 1000 ppl undernourished, and Ghana (HDI 0.611) is 4.5 DALY per 1000 ppl undernourished.

Uncertainty estimates are therefore based on the residuals of the fit of the surface used in the methodology of attributing water withdrawal to DALYs in [11]. It is assumed that other countries represent variance and hence uncertainty in DF_i: if 2019 were to be repeated in a statistical

Annex A

ensemble, then variation of underlying factors outside of HDI (and uncertainty in the determination of HDI) would change the attribution of prevalence of undernutrition to DALYs yr^{-1} $capita^{-1}$ from protein-energy malnutrition. Only data from 2019 was used, the posterior joint distributions of β could be updated from data triples in previous years (potentially sharpening the uncertainty estimate), under the assumption that there is no information loss from previous years (that is, past relationships between DALY yr^{-1} $capita^{-1}$ malnutrition, PoU, and HDI are still valid for the present).

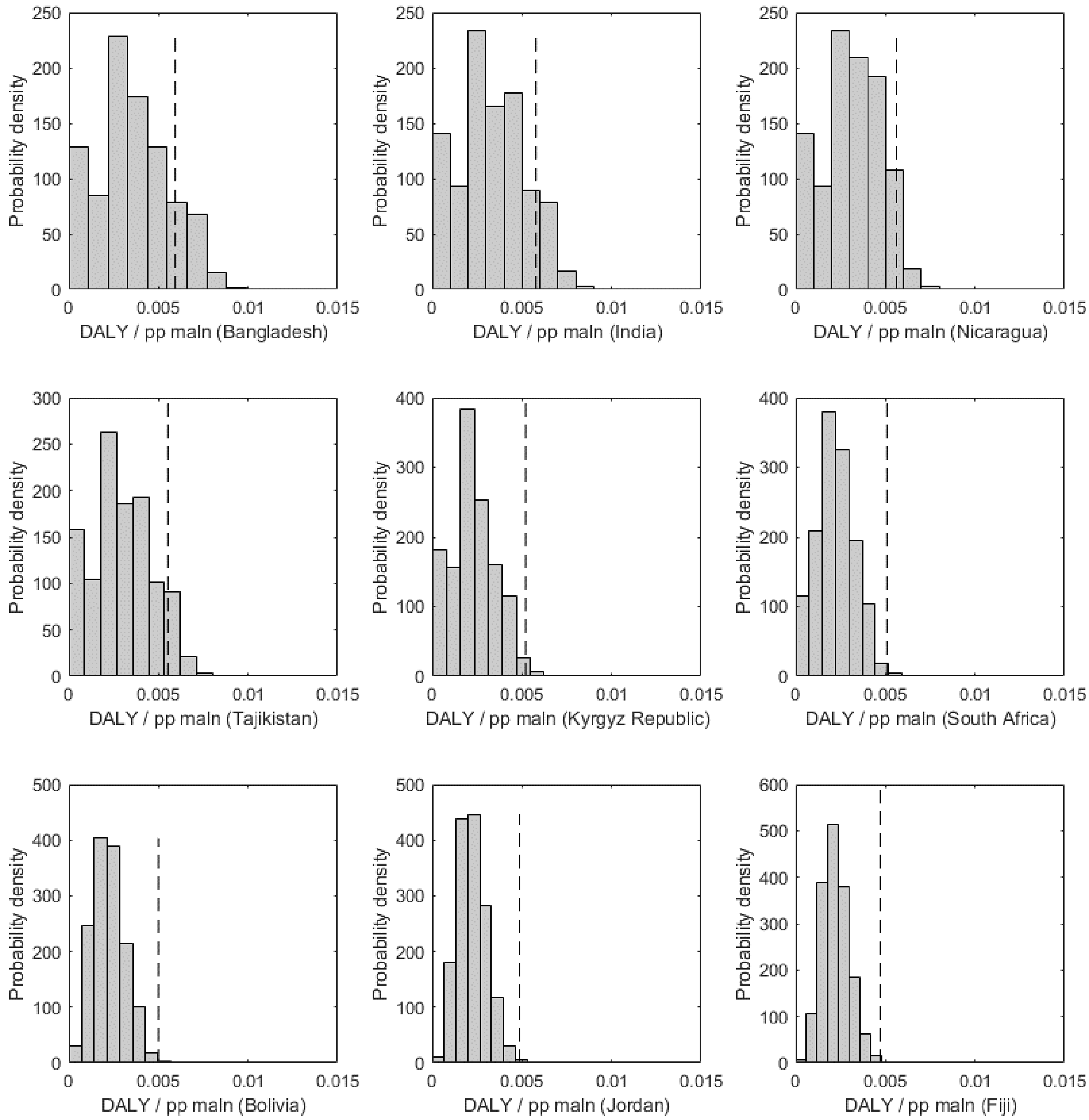

Figure 4: estimate of the factor DF_i in the costs of malnutrition due to water deprivation in 9 example countries 0.625 < HDI < 0.75 with HDI increasing from top left to bottom right. The increasing influence of higher HDI on reducing the chance of DALYs in the presence of malnutrition in the data is reflected in the Bayesian estimates by local quadratic curve fitting and modelling left skew in residuals as HDI increased, both of which the OLS MLE estimates (dashed) do not accounted for in the data.

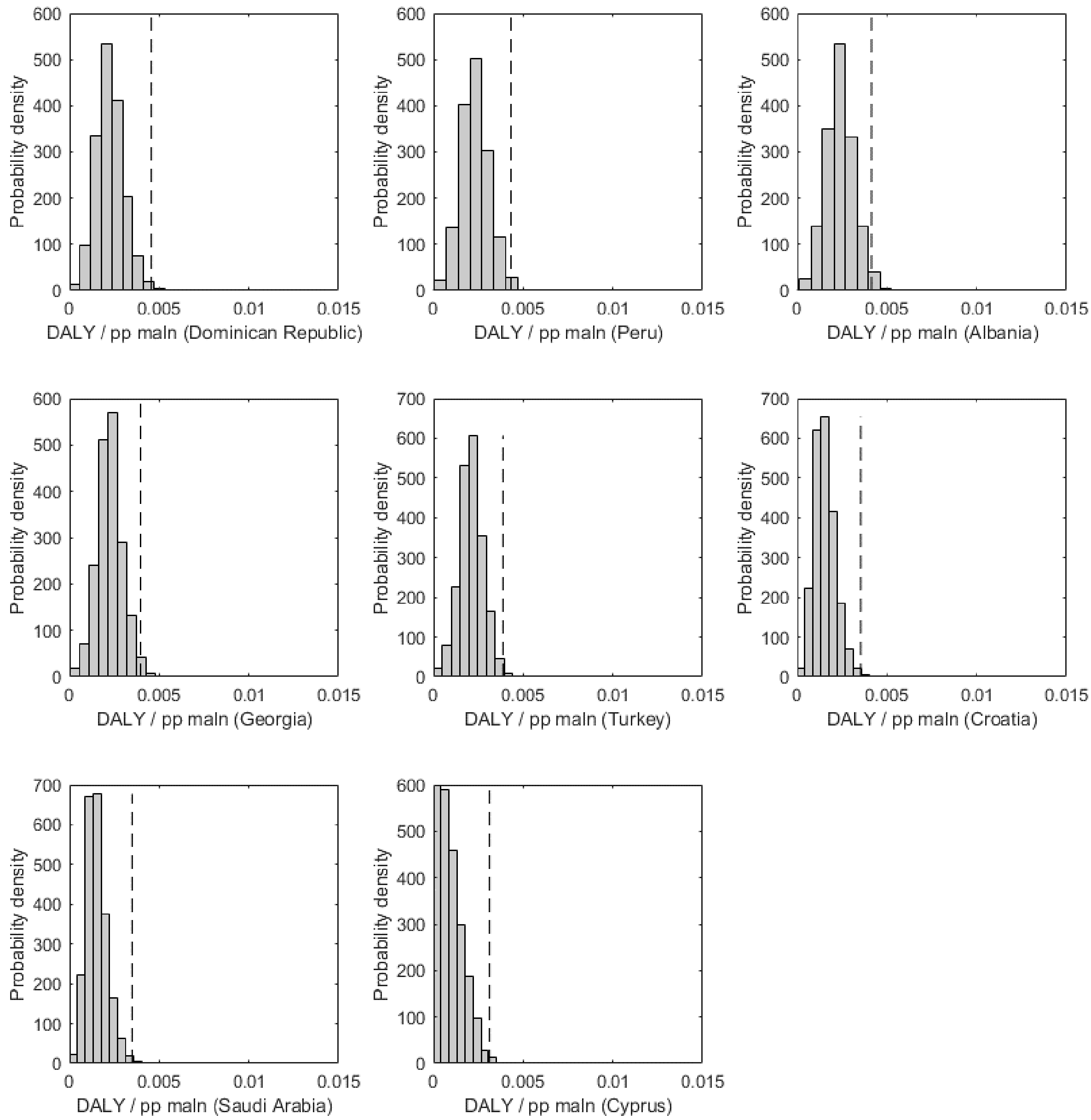

Figure 5: estimate of the factor DF_i in the costs of malnutrition due to water deprivation in 9 example countries 0.75 <= HDI < 0.89 with HDI increasing from top left to bottom right. The influence of higher HDI on reducing the uncertainty in residuals (left panel Figure 11) results in distributions with less variance.

The rate EF_i from [11] is meant to attribute a unit of deprived blue water to agriculture to an amount of reduced food production and then to the number of people experiencing malnutrition because of that lost food production. The value EF_i is estimated in [11] by

$$\frac{HDF_i}{WRI_i}$$

where Water Requirements Indicator $WRI_i = 1300$ m^3 yr^{-1} capita^{-1} deprived, and Human Development Factor HDF_i is a factor representing the vulnerability of the country to deprived food. WRI_i was derived in ([19], p. 58) as a global estimate of the minimum amount of water required of agriculture over a year required to provide nourishment to an individual. The interpretation is that if 1300 m^3 of blue water was deprived, then 1 person's worth of food for an adequate diet is deprived from the country (either directly from subsistence or domestic market, or through income loss).

According to [11] 1 person's worth of food removed from production results in HDF_i number of people malnourished. The motivation for HDF_i is reasonable, that in countries with greater undernourishment and worse development, removing a certain amount of food will result in greater malnutrition and worse outcomes from malnutrition, but the derivation is rather arbitrary. It would seem an improvement to factor through the dietary energy deficiency per capita (cal) and the number of calories per capita lost through that deprived unit of blue water w:

$$EF_i = \frac{\partial PoU}{\partial cal} \cdot \frac{\partial cal}{\partial w}$$

The partial derivative of the FAOs prevalence of undernourishment PoU to cal could be examined from the FAO distributions of dietary energy per capita and the undernourishment cut-off by removing calories equal to $1m^{-3}$ deprived from the distribution (there is some uncertainty where to remove the calories - shift the entire distribution back or lengthen the left tail). Economics would suggest removing calories from the bottom end of the distribution since higher income individuals can afford the higher prices from the reduced supply. The term $\frac{\partial cal}{\partial w}$ could be improved by spatially explicit modelling of water requirements for current irrigated crops and livestock production to meet calorie (or nutrient) needs. Areas of subsistence farming and/or severe food insecurity would be the most important areas for spatial distinction. Even though there are statistical errors in the determination of PoU_i from survey data, the FAO does not publish the uncertainty nor the distributions.

From lack of data we treat EF_i as in [11] and estimate uncertainty. Previous estimates of WRI_i cited in [19] varied $\pm 10\%$. We uniformly vary WRI_i over this range. The calculation of HDF_i involved a quadratic fit of DALY/yr/capita values against HDI (the projection onto the DALY-HDI plane in Figure 2), conditioned on certain knowledge that HDF_i takes the value 1 for HDI < 0.3. The residuals have the same heteroscedasticity observed in Figure 11, and a similar Bayesian quadratic regression (but conditioned on certainty of 1 for HDI = 0.3) was used to represent parameter, and hence model, uncertainty in the quadratic fit (Figure 12). 1000 samples were taken from the distributions for HDF_i and WRI_i and provided 1000 samples for EF_i.

2.5.3 Cost of a DALY from malnutrition

The simplest economic measure of DALYs is to multiply the effective years of life lost by productivity loss [20] [21]. The term CF_i, in \$US2020 PPP $DALY^{-1}$, is from ILO modelled estimates of labour productivity for 2019 for country i belonging to World Bank low-, lower middle-, upper middle-, and high-income bands. As discussed below, under discounting, the future productivity loss from water deprivation would be inflated by an estimate of productivity growth. However, change in HDI over time has not been accounted for in the term DF_i or EF_i, which would reduce DALYs per person being undernourished and reduce the change in the rate of undernourishment produced by water deprivation. Therefore, we do not inflate and keep the simple structure of present damage as a proxy for future amounts.

2.5.4 Income costs from crop losses from water deprivation

The term $VF_{inc,i}$ (US\$2020 PPP / m^3 deprived) of the value loss from crop loss in country i due to a deprived unit of water is calculated from [13]. The reference [13] provides a global spatially explicit dataset, using data on 16 primary crops grown within a spatial cell to attribute the present production value of a unit of water deprived per soil type and per crop using a productivity function approach. The result is translated into monetary amounts using 2019 FAOSTAT farm-gate prices in international dollars.

Annex A

Uncertainties come from: (a) variation in the crops impacted – a concentration of water withdrawals in the region of the highest value crops in country i would result in a higher value per unit withdrawal than taking the average across all spatial cells for country i, (b) variation in farm gate prices, and (c) the impact of lost income.

To account for (a) we could weight crop costs by the proportion of that crop grown in country i relative to the other 15 crops. The probability that a withdrawal in country i is affecting crop j is determined by the relative proportion of production in FAO 2019 data. Beyond this, without the water withdrawal unit w_i being at a greater level of spatial resolution, and data on distributions of crops between catchments in a country, we cannot tell which crops may be affected by deprivation from a withdrawal. The assumption is the water deprivation occurs randomly in the country and will affect agriculture dependent on the water resource.

For (b) we used data on farm gate prices from FAO. The estimates from series of farm-gate prices are weighted by the amount of domestic production (FAO food producer index). Farm gate-prices reflect an underestimate of losses. Using international commodity prices reflects the lost income to growers, but also other workers in the food system in that country (transportation, storage, trading). This overestimates the income effect, not all production is traded or bought by end users at international prices in-country. The law of one price does not apply because of market imperfections, especially in developing countries. We did not inflate the farm-gate prices to a future time when water deprivation creates the crop loss, we assumed the discounting term for growth of the non-agriculture parts of the economy dominates the increase in agricultural incomes. Therefore, we modelled uncertainty in income loss from crop loss by fitting the variation over time in the FAO producer price index for cereals, without modelling the trend.

For (c) additional socio-economic effects, beside lost income, for those deprived by the withdrawal are not counted except for malnutrition. Subsistence farming and farming households with malnutrition are counted in the malnutrition costs from the withdrawal, not in income losses. Households without malnutrition experience only income effects from the withdrawal. Future equilibrium effects are also not considered: reduced supply increases prices and how much the price increase for the production that has not been deprived compensates for loss of income is uncertain. Modelling in [10] shows that, in some catchments, equilibrium effects may compensate entirely for lost income.

The term VF_i, when coupled with water deprivation, represents a damage cost to agricultural production. The benefit of the present agricultural production *enabled* by the water withdrawal factors into the social costs of the water withdrawal, not the damage cost. The reason why damage costs should not be offset by the production benefit to calculate a 'net' damage cost is that abatement of the water withdrawal may be cheaper than foregoing the agricultural production. Foregoing agricultural production is one abatement measure, and not necessarily completely contained in a marginal abatement curve. The 'net' damage cost is an underestimate of the social cost of the water withdrawal, see the further discussion under social cost of water below.

For the uncertainty in (b) we used the country time series of the FAO food producer index from 1991 to 2019. If $mp_i(t)$ is the ten-year moving average of food producer index at year t for country i, then $\frac{p_i(t)}{mp_i(t)} - 1$ reflects uncertain annual percentage variation in crop incomes around a decadal trend. The average η_i of this random variable over ten years reflects uncertainty in decadal trends in food prices. We fit a multivariate normal distribution to the variation for all countries and treat it as the joint distribution of a random variable of percentage variations of annual farm-gate crop income around the trend. Then we averaged across the values for each country from joint sampling of the multivariate normal. We assume no autocorrelation in percentage variation over decades. This allows the simplification, since we take the decadal average, of ignoring short lag autocorrelation in annual residuals to estimate η_i. Normal approximation is valid for smaller percentage changes, we removed outliers in the FAO food producer index series using mean absolute deviation and would truncate $\eta_i \geq -1$ when required (no samples required resampling to implement truncation).

We use η_i to approximate variation around the trend of income lost to water deprivation over the period 2020-2100. Decadal variation is a useful approximation: without a more sophisticated temporal representation of impacts, the discounting, described below, prioritises impacts within the first few decades for a continuous process of surface water impacts, and once-off impacts from groundwater exhaustion are assumed to occur within the span of a decade.

24 out of 182 countries considered did not have marginal water values from [13]. Most of those countries were island states, but the Republic of Congo, Equatorial Guinea, Liberia, Ireland and Iceland were not represented in the dataset of [13]. We used the Western Europe average as a proxy for Ireland and Iceland, and the Sub-Saharan African average as a proxy for the Republic of Congo, Equatorial Guinea, and Liberia. 33 countries out of 182 considered, representing <5% of global value of agricultural production, did not have any data points for the FAO producer index. No relationship could be found between standard deviation of residuals of producer prices on a regional basis, against development indicators such as HDI, GDP, nor drought indicators. The regional mean of the standard deviations was therefore used as an estimate for the 33 countries without data and represents underestimating uncertainty for 33 countries with missing producer index data. The covariance matrix of the 149 countries with data was inflated to a covariance matrix for 182 countries by assuming no covariance for the 33 countries with missing data.

A constant term VF_i^0 for each country i is given by the data set of [13] as the average farm-gate loss in 2019 due to a unit of blue surface or groundwater deprived. We cannot tell in which catchment deprivation is occurring without the withdrawal also having catchment level spatial resolution and we did not want to model this uncertainty since catchment level resolution may be available in many studies. Then

$$VF_i = (1 + \eta_i) \cdot VF_i^0.$$

2.5.5 Estimating the prevalence of malnutrition in agricultural workers

To estimate α_i, neither the FAO Proportion of Undernourishment (PoU) or Food Insecurity Experience Scale (FIES) indicators for all countries distinguish national malnutrition by household income level, nor the predominant household occupation. This would require re-assessment of the PoU or FIES using data at household survey level, which was not available.

Instead, extreme poverty (<US$1.90 per day, World Bank) for agricultural workers was used as a proxy, and indicators from ILO and the World Bank for poverty combined to estimate the prevalence for agricultural workers. Extreme poverty is not a perfect proxy for undernourishment, income explains only about 50% of variation in malnutrition globally [22].

We estimate the percentage β_i of extreme poverty for agricultural workers in a country i and then adjust the resulting distribution for the relationship between extreme poverty and malnutrition to obtain an estimate of malnutrition.

The ILO calculates the percentage of workers in extreme poverty for country i:

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$q_{i,w|p}$ – percentage of workers in extreme poverty for country i, from ILO https://ilostat.ilo.org/topics/working-poor/

We assume workers in agriculture have a greater rate of workers in extreme poverty than in the general economy, so we set $\beta_i^{min} = q_{i,w|p}$.

In order to underestimate marginal damage costs, we require an overestimate of the rate of agriculture workers in extreme poverty. To do this we use ILO and World Bank estimates:

$q_{i,a|w|p}$ – percentage of agriculture workers among workers in extreme poverty for country i, from [23] and based on regional values.

$q_{i,a|w}$ – percentage of agricultural workers amongst all workers for country i, from ILO and World Bank https://data.worldbank.org/indicator/SL.AGR.EMPL.ZS

For 12 outlier countries the ratio $\frac{q_{i,a|w|p}}{q_{i,a|w}}$ was greater 1 . Except for those, using the regional estimates in [23] can then provide an estimate for the extreme poverty percentage in agricultural workers that is larger than the general rate: $\beta_i^{max} = \frac{q_{i,a|w|p}}{q_{i,a|w}} \cdot \ \beta_i^{min}$.

The 12 outlier countries had either very low poverty rates or very high poverty rates with very high rates of workers in agricultures. In the outlier case $\frac{q_{i,a|w|p}}{q_{i,a|w}}$ had a low mean absolute deviation of 0.02 below 1. To underestimate damage costs however, for outliers we chose for β_i^{max} the moderate poverty headcount percentage (<US$3.20 per day, World Bank) as an overestimate of the percentage of agricultural workers in extreme poverty.

The estimate for β_i is a random variable uniformly distribution over the interval $[\beta_i^{min}, \beta_i^{max}]$.

We use the relationship between malnutrition and extreme poverty for the general population to estimate the random variable $\frac{\alpha_i}{\beta_i}$. Data for the prevalence of undernourishment (PoU) between 2000 and 2018 is available from FAO https://data.worldbank.org/indicator/SN.ITK.DEFC.ZS, data on extreme poverty (PoV) for country i amongst the total population between 2000 and 2018 is available from the World Bank https://data.worldbank.org/indicator/SI.POV.DDAY. From a scatterplot of all obtained pairs of PoU and PoV values, the variation is 0.53, indicating that PoV 'explains' 50% of the variation in PoU. To obtain a finer relationship we excluded the minimum values of 2.5% for PoU and PoV values < 1% and grouped the country data points into HDI tiers: very high human development (0.8-1.0), high human development (0.7-0.8), medium human development (0.55-0.7), and low human development (below 0.55). The explanation within HDI tiers is weaker, with only 11% of the variance in PoU explained by PoV in the low human development tier. Therefore, we do not use a single OLS linear regression estimate for PoU against PoV or regression within HDI bands. Dividing the PoU values by PoV values (each tier had over 60 data points) is treated as a sample from the distribution $\frac{\alpha_i}{\beta_i}$ for a country i with HDI belonging to a HDI tier. Distributions were fitted to the samples to estimate the distribution of the uncertain variable $\frac{\alpha_i}{\beta_i}$ by minimising the Akaike information criterion amongst a common set of distributions. For the 3 lowest tiers, a lognormal distribution provided the best fit up to statistical significance. For the very high HDI tier, a Weibull distribution provided the best fit.

The product of $\frac{\alpha_i}{\beta_i}$ and β_i gives an estimate for the uncertain value α_i, distributed according to the product distributions of the distributions for $\frac{\alpha_i}{\beta_i}$ and β_i. Samples of the product > 1 were assumed, for the simple purpose of overestimation of double counting, to indicate $\alpha_i = 1$ and all agricultural workers were experiencing malnutrition.

2.5.6 Estimating the present value of water deprivation losses

Our method uses losses if the deprivation of water occurred in the present as a proxy for future loss from deprivation of water at a future time. To understand the present value of that future loss requires a discounting term. The component WDF_i from [11] has no temporal component for the deprived amount of water. An examination of the effect a water withdrawal would have on water resources in each catchment would be required to understand the temporal distribution of deprivation (withdrawals increasing water salinity in the present or near-term may reduce available water starting in the present, whereas deprivation from a non-renewing aquifer may be delayed until the aquifer is effectively drained physically or the quality of water degrades such that agricultural use is deprived).

Our estimate of ρ_i is a random variable on [0,1] discounting impacts for an unknown amount $WDF_i \cdot w_i$ of water deprivation between 2020 and 2100. The size of the withdrawal is unknown without specific quantity data – we are developing uncertainty in marginal damage cost to be applied across different studies. The proportion of the withdrawal from a surface source or a groundwater source is unknown: (a) we assume that the proportion for withdrawals tends to the observed proportion for total withdrawals in a country as the size of the withdrawal increases. When the impacts occur is unknown: (b) we assume the impacts occur between 2020 and 2100 at a constant rate of deprivation that was linked to the WSI_i of country i. Those countries with greater water stress and greater groundwater withdrawals were assumed to be more likely to have water deprivation impacts sooner than those without.

For (a): first w_i is chosen randomly between 0.1% and 10% of the total freshwater agricultural withdrawal (TU_i) for country i in 0.1% intervals (AQUASTAT).

The proportion of w_i withdrawn from a surface or groundwater source is determined by a Bernoulli experiment with 1000*($\frac{w_i}{TU_i}$) trials (which allocates 0.1% of total withdrawal per trial) and success given by the ratio of surface water withdrawals against total withdrawals for country i. The ratio is from AQUASTAT for all uses and is assumed to hold for agricultural uses. 63 out of 178 countries with total withdrawals in AQUASTAT did not have data on total surface to groundwater withdrawal. The estimate of 42% of all withdrawals of groundwater used as irrigation is the ratio for the countries without data [24].

For (b): if $s_{i,g}$ is the proportion withdrawn from a groundwater source, a Poisson process with rate

$$\lambda_i = \frac{200 \cdot WSI_i \cdot (1 + s_{i,g})}{2100 - 2020}$$

allocates deprivation amounts to individual years. With extreme water stress $WSI_i = 1$ and total reliance on groundwater $s_{i,g} = 1$, then, on average, 100% of the impacts will occur between 2020 and 2040 at an average rate of 5% per year. With moderate water stress WSI_i=0.5 and equal reliance on groundwater $s_{i,g} = 0.5$, on average, 100% of impacts will occur between approximately 2020-2070 at 1.875% per year. With moderate water stress and no withdrawal of present groundwater, then impacts occur, on average, over the period 2020-2100 at 1.25% per year. This allocation from sampling from a Poisson process provides weights to years by allocating percentages of water deprivation to future years.

The sampled weights for the years $t \in [2020,2100]$ are multiplied against the sequence $(1+d_i)^{2020-t}$ and summed. This provides a distribution for the random variable ρ_i. Here d_i is a long-term GDP growth rate for country i.

For d_i we used the future GDP growth projections for the 5 Shared Socioeconomic Pathways (SSPs) over the periods 2020-2040 and 2040-2100 from Table 3 in [25]. [25] uses its own division of countries into high, medium, and low income. Countries were assigned the GDP projections for their income groups. The SSP was sampled at random and represents uncertainty in d_i (representing minimal information, or a lack of knowledge, on which SSP would be the future). An alternative dataset for uncertainty in long-term GDP projections is [26].

The above procedure generated 186 independent random weights over future years for local impact from deprivation in the country's water resources. In each sample from 1000 joint samples of the 186 weights, the same randomly chosen SSP was applied across the 186 country samples (all countries share the future assumed for that sample). In terms of sensitivity, the different long-term interest rates in the SSPs between high income and low-income countries and low groundwater use against high groundwater use can halve the mean value and standard deviation of ρ_i. Present water stress and the proportion of agricultural use of water create more variation between countries than discount rates.

2.6 Fitting the damage costs of water withdrawal

2.6.1 Results

The components of the equation (3) were derived, with uncertainty, in the previous section. The mean value of costs of deprivation from withdrawal US$2020 PPP m^{-3} withdrawn (equation 3) for 158 countries where data was available is listed in Table 2 in Section 2.10. All tables are in Section 2.10. Table 3 lists the malnutrition (equation 1) and income (equation 2) mean damages, without double counting correction and discounting, for comparison. Table 4 lists 17 countries where the malnutrition costs are estimated to outweigh the income costs from crop loss. The marginal costs in Table 2 vary greatly, even across similar countries, due to the many factors represented in equations (1)-(3) and discussed, water stress, cereal crop production, dependence of crop value on irrigation water from surface and groundwater sources (not desalination), and income and development, which are the three most sensitive factor with discounting rate, which is also linked to income and development, fourth.

2.6.2 Box: "Hidden cost" of water withdrawal for agricultural use

Table 3 includes a 'total damage cost' by multiplying the national marginal costs by total water withdrawals from FAOSTAT, and total damage cost as a percentage of agricultural GVA. These are presumptive figures for reference and should be used carefully in terms of comparison to national or the global economy given lack of consideration of social costs and second order effects for large withdrawals. Large withdrawals escalate the value of water resources and changing marginal costs provides socio-economic forces (economic equilibrium forces) to prevent further withdrawal – making the initial estimate of the assumed large quantity of extraction at the given marginal costs an overestimate. An environmental equilibrium would not care about human prices, in which case the large changes water resources may occur, but in that case the marginal damage costs are underestimated. Depending on which equilibria dominates and lag of the feedback of environmental change to socio-economic response, the 'total cost' figures are biased downwards or upwards.

Graphics for countries facing the largest "hidden" water deprivation costs are shown in Figure 7.

It is less valuable to compare the marginal costs across countries, they represent primarily the externalised costs of water use for market corrections in the economies where the costs are borne. They are therefore more usefully compared against economic indicators of the same country. Table 3 provides the amounts for Figure 7 and compares water damage costs against GVA of agriculture for that country. The data from [13] demonstrates a large variation in the value of water as a factor of productivity across crop types and therefore across countries that also vary in their production amounts of the 16 crop types considered in [13]. Large production of rice and soy in Asia, combined with water stress, large amounts of water used in current production practices, and higher farm-gate prices in PPP terms, are reflected in the high damage costs for Japan and China.

Figure 8 to Figure 10 show the marginal cost distributions for some examples from Table 2. In terms of global totals of "hidden cost", then the distributions of the sum of the country costs in Table 2 are shown in Figure 6 for combined values, and for a comparison of malnutrition and income loss.

There is a large variation in the shape of the distributions across countries, from various factors such as: malnutrition costs which create positive skew; and income losses which we approximated by normally distributed residuals to capture correlation in farm-gate price variation. Generally, malnutrition losses dominate at low HDI (Niger, Senegal), with mixed shapes at mid HDI (India, Bolivia) and normal shapes where income loss dominates at high HDI. Where HDI is high and agricultural use of blue water is low, discount rates from the SSPs over the long-term can dominate the uncertainty, resulting in three peaks in samples (Croatia). These artefacts of modelling and demonstrate the variation in the different components of equation (3) across countries. The samples represent an exploration of the spread of values, greater understanding the shape of probable impacts at present value with modelling requires including coupled biophysical and economic models.

2.6.3 Parametric and non-parametric data for risk assessment

Only some of the terms in equation (3) have uncertainty estimates, we consider the other terms uncertain, but do not have forms by which the uncertainty can be specified. Generally, as a product of four random variables in equation (1), and three random variables in equation (3), by the central limit theorem the *shape* of the estimate of $MDC_{mal,i}$ using [11] would be approximately lognormal independent of the *shape* of the uncertainty in the other factors. The *parameters* of the lognormal fit would be affected by the fit of the other parameters. Uncertainty in the other terms would increase the variance in the lognormal fit, so we still consider that the uncertainty derived for $MDC_{water,i}$ from sampling, given the data available and employing the present methodologies of [11] and [13], is likely an underestimate of tail uncertainty.

The sampling data, available in the full SPIQ dataset, provides a non-parametric form for risk assessment.

Parametric forms of distribution are easier to disseminate. A parametric form, using lognormal distributions given the mathematical rationale above, is informed by the mean and standard deviation from the sampling. Table 2 lists the lognormal fits in the last 2 columns. Conceptually, we understand the damage costs of water as a joint distribution across countries. Table 2 therefore describes the marginals for individual countries. The correlation matrix from the sampling data can be used to generate the explicit formula and samples for multivariate lognormal distribution representing the joint distribution of marginal damage costs. The correlation matrix is available in the SPIQ dataset.

2.6.4 Box: Aggregating damage costs across countries

We emphasise that the joint distribution should be used when adding totals across countries. Studies of subsidy repurposing, dietary change, and food waste make changes to impact quantities such as water withdrawals and nitrogen emissions across countries, and when aggregating the effects, the joint distribution should be used to assess risk. Correlations can increase the probability of extreme costs greatly, and so sampling independently from marginals can dramatically underestimate economic risk of food system impacts.

2.6.4 Improvements

This study was framed on using existed datasets and methods to estimate the marginal damage costs of water for individual countries. The approach from [11] is highly cited, and implemented in Lifecycle Impact Assessment software and standards. It does, however, introduce the derived quantity of deprived water without any consideration in temporal aspects of impact. Considering the surface DALY/yr/capita against PoU, HDI, WDF*, PROD, and w, where WDF* represents observable proxies for water scarcity such as total hydrological flow but is not a function of w, PROD is crop production, and w is water withdrawal, could yield an improved analysis and test the validity of the form of the equation in (1). The components PoU, HDI, WDF*, and PROD could be given a reasonable time dependence by attaching hydrological and use changes in WDF*, use changes in PROD, and socioeconomic changes in HDI and PoU from scenarios. The rationale for equations like (1) is that information is gained (uncertainty reduced) by the knowledge of terms in the chain rule expansion. Including PROD explicitly would also increase consistency between the terms $MDC_{mal,i}$ and $MDC_{inc,i}$.

2.7 Double counting and correlations with other impact quantities

The joint distribution of marginal damage costs for water withdrawals across 158 countries (sampled or parametric) described in Section 2.6 and earlier sections considered double counting and correlation within marginal damage costs for agricultural freshwater withdrawal.

Correlation of marginal damage costs of other quantities of impact and sensitivity analysis is described in Annex B. We discuss the interactions of the impacts of water withdrawal with the other quantities here and estimate block correlation coefficients for Table 3 in Annex B.

2.7.1 Interaction with marginal costs of other impact quantities

The interaction between the quantities associated to impact of current activities need to be separated from the interaction between marginal costs given a unit change in either quantity. Modelling, or the method that determines quantity changes, would keep track of joint changes in quantities.

GHG marginal costs and marginal costs of water withdrawal

Joint climate and water modelling shows that present GHG emissions, through temperature increases and change in precipitation patterns, will lead to increased water stress [2, 15, 27]. Economic damage from climate change will also impair HDI increase [28], which factors into marginal increases in undernourishment and prevention of undernourishment leading to DALYs. Direct temperature damage to crops and soil, exacerbates the effects of water deprivation. For water stress, however, modelling found that socio-economic factors such as population growth caused larger variance in outcomes than climate change [15, 29], and uncertainty in climate effects [27]. We use a moderate positive correlation for the block correlation coefficient between marginal damage costs for ppl in extreme poverty and water deprivation in the future is more dependent on socioeconomic changes than climate change.

Land use marginal costs and marginal costs of water withdrawal
Agricultural activities produce a conversion in land use and a change in ecosystem services. The land-use conversion to irrigated agriculture in a water stressed catchment increases water stress. The economic benefits of agriculture can increase HDI and, depending on other socio-economic factors, result in reduction of rates of undernourishment and DALYS due to undernourishment. Increase in extent of agricultural land-use is not itself a strong determinant of HDI, so this negative correlation effect would generally be weaker than the positive correlation between a marginal increase in agricultural use and marginal increase in water stress. Not all countries experience water stress, so, for a block co-efficient, we use a weak positive correlation.

Marginal costs of nitrogen emissions and marginal costs of water withdrawal
With greater water stress the concentrations or exposure of nitrates in groundwater increase. Nitrates form only a small portion of the marginal costs of Nr emissions [30]. Water deprivation resulting in salination and other ecosystem damage will likely exacerbate the acidification and eutrophication of surface freshwater bodies from nitrogen deposition and direct run-off. Positive correlations in damages may only appear at threshold levels: water limitation without ecosystem damage would generally reduce biological growth, but removing N-limitation can sometimes counteract this (which leads to a negative correlation) [31]. Impacts from Nr emissions are short term unless they cause sustained change in biodiversity or ecosystems, which may then intersect with future water deprivation. Freshwater withdrawals would have to compare to green water flows to significantly increase concentration of run-off Nr in waterways, and this effect would only be a third order term. Increased crop prices under normal economic conditions creates increase in fertiliser use. However, this creates a change in the quantity of Nr emissions and only at third order terms would this effect the marginal damage per Nr emissions. We estimate therefore that uncertain crop prices in future decades very weakly interacts with present Nr emissions. Overall, assuming sustained nitrogen use and water stress, we use a weak positive correlation between marginal damage costs for nitrogen emissions and water withdrawal.

Poverty marginal costs and marginal costs of water withdrawal
Extreme poverty explains about 50% of malnutrition [22]. If poverty gaps are higher, then malnutrition will be more prevalent for the same water deprivation, including less income to import virtual water to counter crop loss. We would also expect an effect, through the relationship of HDI with the rate of DALYs from protein-energy malnutrition per undernourished people. The purely income component of the marginal damage costs for water is largest in upper-middle to high income countries where agriculture is a small component of GDP and less agricultural workers overlap with workers in extreme poverty. So marginal damage costs for water decouple from poverty at higher HDI, however the poverty gaps and impacts of poverty per person in poverty are increasing smaller as the decoupling occurs. We use a weak positive correlation for the block correlation coefficient between marginal damage costs for ppl in extreme poverty and water withdrawal.

Chronic and Hidden Hunger marginal costs and marginal costs of water withdrawal
DALYs per undernourished person are a component of the malnutrition associated to water deprivation. There would be a double counting effect if the derivation of the change in undernourishment quantity used in the marginal costs of chronic and hidden hunger included water deprivation. However, we need to consider temporal effects. Undernourishment occurs now from consumption now, but starvation occurs in the short term, and chronic and hidden hunger have health effects in the short and longer tem depending on the age distribution of the undernourished populations. The intersection between water deprivation in the future and calorie and marginal changes in consumption now is therefore in the intersection between long term effects of

consumption now and short term effects of water deprivation, as well as reduced access and quality of drinking water and sanitation in the future [32]. Generally, inadequte energy and nutrients intake will exacerbate existing health conditions [33], if the DALY is indicating disease and not life lost in the temporal gap between the two effects. Uncertainty in the temporal intersection of effects and the larger influence of future socio-economic effects on undernourishment compared to water deprivation, means that we use a weak positive block correlation between the marginal damage costs of water withdrawal and chronic and hidden hunger from current consumption.

Dietary risk marginal costs and marginal costs of water withdrawal
There is no component in the marginal damage costs of water associated to dietary risk factors in the Global Burden of Disease (GBD) study besides general undernourishment. Future poor health from a marginal change in lower consumption of fruits, vegetables and whole grains now, and higher consumption of sugar and salt now, would need to intersect with and exacerbate health effects from future undernourishment or future change in crop prices. Crop prices in the future effect future consumption and can be assumed to be decoupled from consumption now. With the greatest burden of dietary risk factors in mid to higher income countries, the intersection with future malnutrition seems remote. So we find no significant block effect between impacts from unit of water withdrawal now and health impacts from marginal dietary changes now.

2.7.2 Quantification of correlations

Correlation	**P**	
Strong negative	-0.8	
Moderate negative	-0.5	
Weak negative	-0.2	
None	0	
Weak positive	0.2	
Moderate positive	0.5	
Strong positive	0.8	

Table 1: Block Pearson correlation coefficients between uncertain marginal damage costs

Costs of…	GHG emission	Water use	Land use	Nr Emissions	Poverty	NCDs	Chronic & Hidden Hunger
Water use/ depletion	+0.5		+0.2	+0.2	+0.2	0	+0.2

2.8 Social costs of water

The social cost of water, that is, the optimal water withdrawal that maximises the social surplus from the consumption of that water, is difficult to calculate.

A simple estimate would compare damage costs (the externalities of withdrawal) compared to the benefit of the production enabled by withdrawal at, or transported from, the location of withdrawal.

In water stressed areas, with competition between water uses and potential high social costs from impacted food production, human health and sanitation, the social cost may be positive. In areas of abundant water, the damages will more likely be less than benefits.

Like the discussion under the social costs of nitrogen, there is potential ambiguity in the social costs if the units are not defined consistently. The social costs of unit of water consumed uses the point of consumption for evaluation of benefits and costs. Where water has been transported some distance from multiple sources, or even whether embedded water is considered to be consumed at the point of embedding (e.g. production), or consumed when lost in a later process (e.g. eating), then mapping between the locations of withdrawal and proportions of water withdrawn for a unit of water consumption is a complicated tasks. It is also complicated to understand the relationship between abatement of the consumption quantity (i.e. eating less red meat and dairy) in relation to abatement measures of water withdrawal.

For tractability, a unit of water at location withdrawn is more derivable and applicable for a general dataset of damage costs. Actors in the food system can estimate where the water withdrawal has occurred for the consumption in their activities.

The social cost of water is underestimated without the full range of abatement measures and exclusive damages being considered. The social cost of water is overestimated when damages include double counting (are not exclusive). Foregoing the benefit of the production enabled by withdrawal at, or transported from, the location of withdrawal is not necessarily the lowest cost abatement measure. Determining the social cost of water withdrawn at a particular location, which for pragmatism would be the catchment level, requires determination of abatement cost curves and the marginal abatement cost. Many abatement measures, including Water Use Efficiency (WUE), are abating water consumption. Understanding the full spectrum of abatement measures available to obtain the abatement curve at a point of withdrawal (which lists abatement measures by their least cost per international dollar to abate a unit of withdrawal) is complex.

Dietary change can be considered a form of water-use efficiency, where the ultimate product is human diets of the same or greater utility to consumers. Saved consumption from dietary change would need to be traced back to the water withdrawn to produce foods – which has been done by models.

At the other end of the spectrum of distance between withdrawal and consumption is shifting production (assuming same diet) so that less water is withdrawn. The present global distribution of crops are not optimal from the view of water availability [12], crop requirements, and economic return [13]. ‘Water sparing’ – a global redistribution of production to optimise water use would abate withdrawals at locations of scarcity. However, the costs and political feasibility of shifting production face similar challenges to estimate as the costs and political feasibility of shifting consumption. ‘Water sparing’ also needs to match optimised redistribution of land-use and fertiliser use.

The ‘true’ social costs of water are not discoverable, what is required are estimates which can sponsor economic action of appropriate magnitude. A useful estimate requires value of environmental flows, and local estimates of abatement costs. The present water withdrawal damage cost focusses on income losses, or near proxies to income losses, from crops in water scarce catchments. Abating by the simplest measures available, and used in some studies, which is the benefit foregone by production created from the withdrawal, leads to adding and subtracting potentially similar amounts.

Studies have used abatement costs of water withdrawal as proxies for the social cost of water. This likely significantly underestimates the value component of water in water scarce areas which is a component of the social cost. Marginal abatement costs only become substitutable for the social costs at the optimal level of withdrawal.

2.9 Considerations for use

Models may include estimates of water withdrawal on present or future irrigated agricultural production in catchments or lack feedback between water withdrawal and water limited production.

In the absence of endogenous correction of agricultural production for water scarcity, then the valuations in [11] and [13] represent a first order correction. They can be applied to estimates of water withdrawal changes derived from production changes. Potential inconsistencies include:

- costing the water withdrawal does not correct production or any of the other costs associated directly or indirectly to agricultural production, including
- a different methodology used to calculate malnutrition effects from the endogenous calculation of agricultural production
- potential double counting with the damage costs of poverty.

2.10 References

1. Shiklomanov, I.A., *World Water Resources at the Beginning of the 21st Century*. 2003, Cambridge: Cambridge University Press.
2. Schlosser, C.A., et al., *The future of global water stress: An integrated assessment.* Earth's Future, 2014. **2**(8): p. 341-361.
3. Falkenmark, M., *Growing water scarcity in agriculture: future challenge to global water security.* Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 2013. **371**(2002): p. 20120410.
4. Mateo-Sagasta, J., et al., *Water pollution from agriculture: a global review. Executive summary*. 2017, Food and Agriculture Organization of the United Nations. International Water Management Institute.: Rome.
5. EEA, *Industrial waste water treatment - pressures on Europe's ennvironment*, in *EEA Report*. 2018, European Environment Agency: Copenhagen, Denmark.
6. OECD, *Pharmaceutical Residues in Freshwater*, in *OECD Studies on Water*. 2019, OECD Publishing: Paris.
7. Thebo, A.L., et al., *A global, spatially-explicit assessment of irrigated croplands influenced by urban wastewater flows.* Environmental Research Letters, 2017. **12**(7): p. 074008.
8. Rost, S., et al., *Agricultural green and blue water consumption and its influence on the global water system.* Water Resources Research, 2008. **44**(9).
9. Heinke, J., et al., *Water Use in Global Livestock Production—Opportunities and Constraints for Increasing Water Productivity.* Water Resources Research, 2020. **56**(12): p. e2019WR026995.
10. Dolan, F., et al., *Evaluating the economic impact of water scarcity in a changing world.* Nature Communications, 2021. **12**(1): p. 1915.
11. Pfister, S., A. Koehler, and S. Hellweg, *Assessing the Environmental Impacts of Freshwater Consumption in LCA.* Environmental Science & Technology, 2009. **43**(11): p. 4098-4104.
12. Rosa, L., et al., *Global agricultural economic water scarcity.* Science Advances, 2020. **6**(18): p. eaaz6031.
13. D'Odorico, P., et al., *The global value of water in agriculture.* Proceedings of the National Academy of Sciences, 2020. **117**(36): p. 21985.
14. Vollmer, D. and I.J. Harrison, *H2O ≠ CO2: framing and responding to the global water crisis.* Environmental Research Letters, 2021. **16**(1): p. 011005.
15. Vörösmarty, C.J., et al., *Global Water Resources: Vulnerability from Climate Change and Population Growth.* Science, 2000. **289**(5477): p. 284.
16. Alcamo, J., et al., *Development and testing of the WaterGAP 2 global model of water use and availability.* Hydrological Sciences Journal, 2003. **48**(3): p. 317-337.
17. Healy, J., *For farms in the West, oil wells are thirsty rivals.* The New York Times, 2012. **5**.
18. Gödecke, T., A.J. Stein, and M. Qaim, *The global burden of chronic and hidden hunger: Trends and determinants.* Global Food Security, 2018. **17**: p. 21-29.
19. Falkenmark, M. and J. Rockström, *Balancing Water for Humans and Nature: The New Approach in Ecohydrology*. 2004, London: Earthscan.
20. Cleaver, K., N. Okidegbe, and E. De Nys, *Agriculture and rural development: Hunger and malnutrition*, in *World Bank Seminar Series: Global Issues Facing Humanity*. 2006, The World Bank: Washington, DC. p. 1-18.
21. Global Panel, *The Cost of Malnutrition: Why Policy Action is Urgent* in *Technical Brief*. 2016, Global Panel on Agriculture and Food Systems for Nutrition: London.
22. FAO, *State of food insecurity in the world 2013: the multiple dimensions of food security*. 2013, Rome: Food Agriculture Organization of the United Nations.
23. Castaneda, A., et al., *Who Are the Poor in the Developing World?*, in *Policy Research Working Paper*. 2016, World Bank: Washington, DC.

24. Döll, P., et al., *Impact of water withdrawals from groundwater and surface water on continental water storage variations.* Journal of Geodynamics, 2012. **59-60**: p. 143-156.
25. Leimbach, M., et al., *Future growth patterns of world regions – A GDP scenario approach.* Global Environmental Change, 2017. **42**: p. 215-225.
26. Christensen, P., K. Gillingham, and W. Nordhaus, *Uncertainty in forecasts of long-run economic growth.* Proceedings of the National Academy of Sciences, 2018. **115**(21): p. 5409.
27. Schewe, J., et al., *Multimodel assessment of water scarcity under climate change.* Proceedings of the National Academy of Sciences, 2014. **111**(9): p. 3245.
28. Mendelsohn, R., *The Impact of Climate Change on Agriculture in Developing Countries.* Journal of Natural Resources Policy Research, 2008. **1**(1): p. 5-19.
29. Graham, N.T., et al., *Humans drive future water scarcity changes across all Shared Socioeconomic Pathways.* Environmental Research Letters, 2020. **15**(1): p. 014007.
30. Erisman, J.W., et al., *Consequences of human modification of the global nitrogen cycle.* Philosophical transactions of the Royal Society of London. Series B, Biological sciences, 2013. **368**(1621): p. 20130116-20130116.
31. Zhou, X., et al., *Combined effects of nitrogen deposition and water stress on growth and physiological responses of two annual desert plants in northwestern China.* Environmental and Experimental Botany, 2011. **74**: p. 1-8.
32. Dobe, M., *Viewpoint: The role of sanitation in malnutrition – A science and policy controversy in India.* Journal of Public Health Policy, 2015. **36**(1): p. 7-14.
33. Müller, O. and M. Krawinkel, *Malnutrition and health in developing countries.* CMAJ : Canadian Medical Association journal = journal de l'Association medicale canadienne, 2005. **173**(3): p. 279-286.

Annex A

2.11 Appendix

2.11.1 Tables of results

Table 2: Marginal damage costs (MDC) from agricultural water withdrawal in 164 countries. Measured in US$2020 purchasing power parity (international dollars) per 1000 m^3 of withdrawal (megalitre). The parameters mu and sigma refer to the lognormal fit to the MDC per m^3 as an uncertain value: log(MDC)~N(mu,sigma).

Country	ISO3166-1	UN M49	HDI	WSI	MDC US$2020 PPP per 1000 m3 (Megalitre)	mu	sigma
Afghanistan	AFG	4	0.511	0.966	**19.5**	-3.943	0.262
Angola	AGO	24	0.581	0.019	**0.03**	-10.512	0.564
Albania	ALB	8	0.795	0.131	**5.7**	-5.218	0.329
United Arab Emirates	ARE	784	0.89	0.998	**241.36**	-1.423	0.056
Argentina	ARG	32	0.845	0.352	**13.03**	-4.364	0.22
Armenia	ARM	51	0.776	0.983	**170.08**	-1.772	0.084
Australia	AUS	36	0.944	0.402	**45.04**	-3.112	0.15
Austria	AUT	40	0.922	0.096	**0.83**	-7.128	0.272
Azerbaijan	AZE	31	0.756	0.903	**41.3**	-3.185	0.125
Burundi	BDI	108	0.433	0.012	**0.15**	-9.309	1.063
Belgium	BEL	56	0.931	0.715	**2.06**	-6.191	0.104
Benin	BEN	204	0.545	0.018	**0.17**	-9.19	1.037
Burkina Faso	BFA	854	0.452	0.015	**0.3**	-8.65	1.094
Bangladesh	BGD	50	0.632	0.499	**11.8**	-4.429	0.244
Bulgaria	BGR	100	0.816	0.389	**5.58**	-5.209	0.214
Bahrain	BHR	48	0.852	1	**59.43**	-2.825	0.056
Bosnia and Herzegovina	BIH	70	0.78	0.077	**0.5**	-7.654	0.33
Belarus	BLR	112	0.823	0.076	**1.33**	-6.688	0.37
Belize	BLZ	84	0.716	0.01	**0.14**	-9.409	1.362
Bolivia	BOL	68	0.718	0.369	**44.32**	-3.176	0.47
Brazil	BRA	76	0.765	0.066	**1.23**	-6.813	0.555
Brunei Darussalam	BRN	96	0.838	0.01	**0.01**	-11.569	0.327
Bhutan	BTN	64	0.654	0.017	**0.5**	-7.675	0.419
Botswana	BWA	72	0.735	0.675	**5.05**	-5.442	0.745
Central African Republic	CAF	140	0.397	0.01	**0**	-13.858	1.049
Canada	CAN	124	0.929	0.102	**0.88**	-7.068	0.278
Switzerland	CHE	756	0.955	0.092	**8.61**	-4.787	0.26
Chile	CHL	152	0.851	0.736	**56.15**	-2.889	0.115
China	CHN	156	0.761	0.478	**31.64**	-3.466	0.189
Cote d'Ivoire	CIV	384	0.538	0.012	**0.07**	-9.979	0.974
Cameroon	CMR	120	0.563	0.011	**0.17**	-8.848	0.683
Congo, Dem. Rep.	COD	180	0.48	0.01	**0.06**	-10.403	1.195
Congo, Rep.	COG	178	0.574	0.01	**0.01**	-12.879	1.287
Colombia	COL	170	0.767	0.037	**0.75**	-7.279	0.449
Cabo Verde	CPV	132	0.665	0.01	**0.76**	-7.647	0.989
Costa Rica	CRI	188	0.81	0.016	**0.49**	-7.703	0.414

Cuba	CUB	192	0.783	0.228	**22.25**	-3.836	0.256
Cyprus	CYP	196	0.887	0.875	**300.31**	-1.205	0.051
Czech Republic	CZE	203	0.9	0.144	**3.78**	-5.607	0.249
Germany	DEU	276	0.947	0.12	**0.7**	-7.293	0.259
Djibouti	DJI	262	0.524	0.04	**0.08**	-9.766	0.828
Denmark	DNK	208	0.94	0.069	**11.81**	-4.472	0.266
Dominican Republic	DOM	214	0.756	0.114	**2.32**	-6.116	0.345
Algeria	DZA	12	0.748	0.79	**71.3**	-2.642	0.09
Ecuador	ECU	218	0.759	0.18	**5.01**	-5.346	0.387
Egypt, Arab Rep.	EGY	818	0.707	0.977	**40.87**	-3.195	0.119
Eritrea	ERI	232	0.459	0.614	**64.07**	-2.83	0.483
Spain	ESP	724	0.904	0.715	**123.4**	-2.096	0.088
Estonia	EST	233	0.892	0.027	**0.02**	-10.831	0.32
Ethiopia	ETH	231	0.485	0.205	**7**	-5.077	0.492
Finland	FIN	246	0.938	0.416	**5.86**	-5.153	0.167
France	FRA	250	0.901	0.181	**6.77**	-5.019	0.231
Gabon	GAB	266	0.703	0.01	**0.1**	-9.339	0.43
United Kingdom	GBR	826	0.932	0.395	**70.3**	-2.667	0.156
Georgia	GEO	268	0.812	0.683	**82.36**	-2.508	0.159
Ghana	GHA	288	0.611	0.055	**1.18**	-6.859	0.596
Guinea	GIN	324	0.477	0.018	**0.14**	-9.279	0.957
Gambia, The	GMB	270	0.496	0.016	**0.08**	-9.85	0.945
Guinea-Bissau	GNB	624	0.48	0.012	**0.09**	-9.825	1.03
Equatorial Guinea	GNQ	226	0.592	0.01	**0.02**	-10.747	0.501
Greece	GRC	300	0.888	0.711	**272.15**	-1.305	0.067
Guatemala	GTM	320	0.663	0.012	**1.48**	-6.617	0.492
Guyana	GUY	328	0.682	0.011	**2.81**	-5.975	0.469
Honduras	HND	340	0.634	0.013	**0.72**	-7.962	1.482
Croatia	HRV	191	0.851	0.055	**1.04**	-6.91	0.287
Haiti	HTI	332	0.51	0.051	**1.6**	-6.749	0.816
Hungary	HUN	348	0.854	0.095	**1.91**	-6.297	0.281
Indonesia	IDN	360	0.718	0.18	**9.03**	-4.758	0.353
India	IND	356	0.645	0.967	**59.19**	-2.846	0.32
Ireland	IRL	372	0.955	0.022	**1.84**	-6.343	0.318
Iran, Islamic Rep.	IRN	364	0.783	0.912	**64.27**	-2.742	0.076
Iraq	IRQ	368	0.674	0.974	**23.13**	-3.732	0.195
Iceland	ISL	352	0.949	0.01	**0**	-12.41	0.321
Israel	ISR	376	0.919	0.996	**198.68**	-1.619	0.071
Italy	ITA	380	0.892	0.273	**36.15**	-3.335	0.176
Jamaica	JAM	388	0.734	0.013	**0.47**	-7.759	0.428
Jordan	JOR	400	0.729	0.973	**39**	-3.236	0.09
Japan	JPN	392	0.919	0.323	**150.65**	-1.909	0.182
Kazakhstan	KAZ	398	0.825	0.616	**20.49**	-3.899	0.163
Kenya	KEN	404	0.601	0.021	**0.22**	-9.003	1.195

Kyrgyz Republic	KGZ	417	0.697	0.997	**86.42**	-2.449	0.116
Cambodia	KHM	116	0.594	0.089	**6.49**	-5.342	0.869
Korea, Rep.	KOR	410	0.916	0.597	**67.62**	-2.7	0.111
Kuwait	KWT	414	0.806	1	**108.34**	-2.216	0.054
Lao PDR	LAO	418	0.613	0.025	**0.49**	-7.783	0.719
Lebanon	LBN	422	0.744	0.83	**61.52**	-2.788	0.091
Liberia	LBR	430	0.48	0.01	**0.02**	-11.431	1.078
Libya	LBY	434	0.724	0.988	**57.49**	-2.845	0.062
Sri Lanka	LKA	144	0.782	0.611	**16.19**	-4.123	0.128
Lesotho	LSO	426	0.527	0.993	**7.32**	-4.915	0.18
Lithuania	LTU	440	0.882	0.035	**1.2**	-6.775	0.315
Luxembourg	LUX	442	0.916	0.1	**0.12**	-9.065	0.262
Latvia	LVA	428	0.866	0.019	**1.36**	-6.646	0.321
Morocco	MAR	504	0.686	0.844	**43.07**	-3.14	0.107
Moldova	MDA	498	0.75	0.143	**0.7**	-7.306	0.319
Madagascar	MDG	450	0.528	0.028	**0.26**	-8.745	1.072
Mexico	MEX	484	0.779	0.756	**25.3**	-3.682	0.216
North Macedonia	MKD	807	0.774	0.526	**48.11**	-3.048	0.179
Mali	MLI	466	0.434	0.269	**4.4**	-5.548	0.53
Myanmar	MMR	104	0.583	0.018	**0.89**	-7.105	0.418
Montenegro	MNE	499	0.829	0.098	**0.2**	-8.553	0.328
Mongolia	MNG	496	0.737	0.053	**2.71**	-5.975	0.359
Mozambique	MOZ	508	0.456	0.197	**1.61**	-6.547	0.536
Mauritania	MRT	478	0.546	0.085	**2.79**	-5.925	0.345
Malawi	MWI	454	0.483	0.012	**0.04**	-10.599	0.978
Malaysia	MYS	458	0.81	0.043	**0.84**	-7.156	0.391
Namibia	NAM	516	0.646	0.018	**0.19**	-8.708	0.683
Niger	NER	562	0.394	0.171	**3.33**	-5.808	0.48
Nigeria	NGA	566	0.539	0.298	**6.26**	-5.116	0.388
Nicaragua	NIC	558	0.66	0.03	**0.14**	-8.984	0.549
Netherlands	NLD	528	0.944	0.306	**0.88**	-7.048	0.192
Norway	NOR	578	0.957	0.084	**36.84**	-3.335	0.268
Nepal	NPL	524	0.602	1	**26.47**	-3.645	0.401
New Zealand	NZL	554	0.931	0.023	**3.99**	-5.571	0.315
Oman	OMN	512	0.813	0.982	**187.45**	-1.67	0.038
Pakistan	PAK	586	0.557	0.967	**27.85**	-3.557	0.228
Panama	PAN	591	0.815	0.012	**0.07**	-9.721	0.414
Peru	PER	604	0.777	0.716	**64.02**	-2.767	0.256
Philippines	PHL	608	0.718	0.396	**14.8**	-4.234	0.239
Poland	POL	616	0.88	0.07	**0.88**	-7.076	0.296
Puerto Rico	PRI	630	0.845	0.014	**0.1**	-9.225	0.329
Korea, Dem. People's Rep.	PRK	408	0.733	0.365	**12.25**	-4.779	1.288
Portugal	PRT	620	0.864	0.573	**73.9**	-2.611	0.087
Paraguay	PRY	600	0.728	0.013	**0.18**	-8.716	0.429

West Bank and Gaza	PSE	275	0.708	0.999	**102.76**	-2.853	1.67
Qatar	QAT	634	0.848	1	**6.76**	-5.003	0.073
Romania	ROU	642	0.828	0.099	**1.11**	-6.865	0.359
Russian Federation	RUS	643	0.824	0.111	**0.99**	-6.98	0.346
Rwanda	RWA	646	0.543	0.023	**0.36**	-8.37	0.987
Saudi Arabia	SAU	682	0.854	0.995	**21.01**	-3.872	0.048
Sudan	SDN	729	0.51	0.318	**3.91**	-5.596	0.404
Senegal	SEN	686	0.512	0.113	**1.04**	-7.037	0.687
Sierra Leone	SLE	694	0.452	0.011	**0.03**	-10.862	1.004
El Salvador	SLV	222	0.673	0.016	**0.41**	-7.885	0.415
Somalia	SOM	706	0.285	0.15	**2.36**	-6.327	0.709
Serbia	SRB	688	0.806	0.098	**1.11**	-6.866	0.35
South Sudan	SSD	728	0.433	0.318	**1.75**	-6.412	0.428
Suriname	SUR	740	0.738	0.014	**0.05**	-10.436	1.056
Slovak Republic	SVK	703	0.86	0.093	**1.26**	-6.706	0.259
Slovenia	SVN	705	0.917	0.095	**0.08**	-9.431	0.274
Sweden	SWE	752	0.945	0.04	**1.27**	-6.709	0.307
Eswatini	SWZ	748	0.611	0.024	**1.64**	-7.424	1.784
Syrian Arab Republic	SYR	760	0.567	0.999	**11.95**	-4.658	0.775
Chad	TCD	148	0.398	0.027	**0.26**	-8.649	0.901
Togo	TGO	768	0.515	0.015	**0.03**	-10.999	0.992
Thailand	THA	764	0.777	0.534	**14.98**	-4.199	0.166
Tajikistan	TJK	762	0.668	0.999	**96.21**	-2.361	0.283
Turkmenistan	TKM	795	0.715	0.995	**37.28**	-3.273	0.118
Timor-Leste	TLS	626	0.606	0.01	**0.23**	-8.564	0.733
Trinidad and Tobago	TTO	780	0.796	0.506	**0.23**	-8.275	0.22
Tunisia	TUN	788	0.74	0.907	**37.81**	-3.274	0.12
Turkey	TUR	792	0.82	0.779	**162.23**	-1.828	0.148
Tanzania	TZA	834	0.529	0.013	**0.15**	-9.218	0.978
Uganda	UGA	800	0.544	0.023	**0.18**	-9.026	0.934
Ukraine	UKR	804	0.779	0.3	**4.88**	-5.35	0.249
Uruguay	URY	858	0.817	0.012	**0.46**	-7.719	0.333
United States	USA	840	0.926	0.499	**36.46**	-3.32	0.135
Uzbekistan	UZB	860	0.72	0.985	**65.81**	-2.767	0.42
Venezuela, RB	VEN	862	0.711	0.295	**20.24**	-5.674	2.374
Vietnam	VNM	704	0.704	0.35	**14.47**	-4.257	0.238
Yemen, Rep.	YEM	887	0.47	0.942	**55.74**	-2.911	0.29
South Africa	ZAF	710	0.709	0.687	**9.03**	-5.223	1.196
Zambia	ZMB	894	0.584	0.012	**0.07**	-9.725	0.635
Zimbabwe	ZWE	716	0.571	0.192	**2.06**	-6.344	0.675

Annex A

Table 3: Comparisons in marginal damage costs from water use in agriculture. Malnutrition (equation 1) and income components (equation 2) in columns 4 and 5, a total damage costs by multiplying against all agricultural water withdrawals in 2019 (AQUASTAT) in column 6, and the percentage of damage cost against agricultural GVA (missing values implies GVA was not available).

Country	ISO 3166-1	MDC US$2020 PPP per 1000 m3 (Megalitre)	MDC Maln US$2020 PPP per 1000 m3 (Megalitre)	MDC Inc US$2020 PPP per 1000 m3 (Megalitre)	Damage cost using total ag water withdrawals US$2020 1000s	Percent of damage costs against GVA ag
Afghanistan	AFG	**19.5**	11.48	26.85	388308	8%
Angola	AGO	**0.03**	0.08	0.09	4	0%
Albania	ALB	**5.7**	0.19	17.53	4319	0%
United Arab Emirates	ARE	**241.36**	0	276.09	512258	17%
Argentina	ARG	**13.03**	0.28	27.23	362992	1%
Armenia	ARM	**170.08**	1.94	253.61	361654	22%
Australia	AUS	**45.04**	0	63.5	455546	2%
Austria	AUT	**0.83**	0	1.52	64	0%
Azerbaijan	AZE	**41.3**	2.15	63.42	382857	14%
Burundi	BDI	**0.15**	0.24	1.15	34	0%
Belgium	BEL	**2.06**	0	2.61	93	0%
Benin	BEN	**0.17**	0.1	1.22	5	0%
Burkina Faso	BFA	**0.3**	0.17	2.29	126	0%
Bangladesh	BGD	**11.8**	4.17	17.02	371759	1%
Bulgaria	BGR	**5.58**	0.09	11.85	4658	0%
Bahrain	BHR	**59.43**	0.95	67	3042	3%
Bosnia and Herzegovina	BIH	**0.5**	0.01	1.52	10	0%
Belarus	BLR	**1.33**	0.03	4.14	573	0%
Belize	BLZ	**0.14**	0.02	0.98	10	0%
Bolivia	BOL	**44.32**	0.9	105.18	85101	2%
Brazil	BRA	**1.23**	0.12	4.85	48454	0%
Brunei Darussalam	BRN	**0.01**	0	0.02	0	0%
Bhutan	BTN	**0.5**	0.11	1.77	160	0%
Botswana	BWA	**5.05**	0.99	12.02	349	0%
Central African Republic	CAF	**0**	0	0.01	0	0%
Canada	CAN	**0.88**	0	1.64	2339	0%
Switzerland	CHE	**8.61**	0	15.63	1378	0%
Chile	CHL	**56.15**	1.78	70.49	1649133	16%
China	CHN	**31.64**	0.96	59.56	12060545	1%
Cote d'Ivoire	CIV	**0.07**	0.14	0.32	43	0%
Cameroon	CMR	**0.17**	0.17	0.78	125	0%
Congo, Dem. Rep.	COD	**0.06**	0.02	0.5	4	0%
Congo, Rep.	COG	**0.01**	0.01	0.07	0	0%

Colombia	COL	**0.75**	0.05	2.96	4816	0%
Cabo Verde	CPV	**0.76**	0.05	4.55	18	0%
Costa Rica	CRI	**0.49**	0.02	1.84	1133	0%
Cuba	CUB	**22.25**	0.37	54.44	100525	3%
Cyprus	CYP	**300.31**	1.09	350.22	38377	9%
Czech Republic	CZE	**3.78**	0	6.68	176	0%
Germany	DEU	**0.7**	0	1.26	210	0%
Djibouti	DJI	**0.08**	0.18	0.31	0	0%
Denmark	DNK	**11.81**	0	21.56	3859	0%
Dominican Republic	DOM	**2.32**	0.31	7.15	17527	0%
Algeria	DZA	**71.3**	0.97	105.12	445657	2%
Ecuador	ECU	**5.01**	0.47	14.81	40446	0%
Egypt, Arab Rep.	EGY	**40.87**	2.32	64.88	2077132	6%
Eritrea	ERI	**64.07**	11.85	155.52	35240	
Spain	ESP	**123.4**	0	155.51	2513126	7%
Estonia	EST	**0.02**	0	0.04	0	0%
Ethiopia	ETH	**7**	3.06	21.97	67766	0%
Finland	FIN	**5.86**	0	8.72	1029	0%
France	FRA	**6.77**	0	11.6	21087	0%
Gabon	GAB	**0.1**	0.02	0.36	4	0%
United Kingdom	GBR	**70.3**	0	101.16	83154	0%
Georgia	GEO	**82.36**	0.69	151.16	87374	8%
Ghana	GHA	**1.18**	0.53	4.5	1251	0%
Guinea	GIN	**0.14**	0.16	0.77	42	0%
Gambia, The	GMB	**0.08**	0.09	0.39	3	0%
Guinea-Bissau	GNB	**0.09**	0.15	0.56	12	0%
Equatorial Guinea	GNQ	**0.02**	0.02	0.09	0	0%
Greece	GRC	**272.15**	1.19	327.04	2460487	32%
Guatemala	GTM	**1.48**	0.08	6.03	2799	0%
Guyana	GUY	**2.81**	0.09	11.23	3829	0%
Honduras	HND	**0.72**	0.09	6.07	851	0%
Croatia	HRV	**1.04**	0.02	1.94	74	0%
Haiti	HTI	**1.6**	1.59	7.98	1939	0%
Hungary	HUN	**1.91**	0.03	3.52	991	0%
Indonesia	IDN	**9.03**	0.41	27.79	1713372	1%
India	IND	**59.19**	6.94	97.11	34648087	7%
Ireland	IRL	**1.84**	0	3.65	290	0%
Iran, Islamic Rep.	IRN	**64.27**	1.12	74.99	5506689	18%
Iraq	IRQ	**23.13**	8.46	26.25	815552	11%
Iceland	ISL	**0**	0	0.01	0	0%
Israel	ISR	**198.68**	0	230.05	129028	3%

Italy	ITA	**36.15**	0	55.28	611928	2%
Jamaica	JAM	**0.47**	0	1.83	53	0%
Jordan	JOR	**39**	2.27	57.42	18725	1%
Japan	JPN	**150.65**	0	234.64	8176802	13%
Kazakhstan	KAZ	**20.49**	0.54	36.25	284486	4%
Kenya	KEN	**0.22**	0.27	1.81	715	0%
Kyrgyz Republic	KGZ	**86.42**	3.16	132.06	617366	60%
Cambodia	KHM	**6.49**	1.44	34.39	13333	0%
Korea, Rep.	KOR	**67.62**	0	89.63	1163557	4%
Kuwait	KWT	**108.34**	3.47	124.86	51958	10%
Lao PDR	LAO	**0.49**	0.3	2.16	3473	0%
Lebanon	LBN	**61.52**	1.18	91.03	42406	3%
Liberia	LBR	**0.02**	0.01	0.14	0	0%
Libya	LBY	**57.49**	3.81	80.3	273589	
Sri Lanka	LKA	**16.19**	0.72	26.08	183098	3%
Lesotho	LSO	**7.32**	2.32	10.26	28	0%
Lithuania	LTU	**1.2**	0.02	2.3	71	0%
Luxembourg	LUX	**0.12**	0	0.21	0	0%
Latvia	LVA	**1.36**	0.02	2.69	84	0%
Morocco	MAR	**43.07**	3.09	64.61	399716	3%
Moldova	MDA	**0.7**	0.03	2.04	30	0%
Madagascar	MDG	**0.26**	0.23	2.15	3445	0%
Mexico	MEX	**25.3**	1.48	42.35	1690130	4%
North Macedonia	MKD	**48.11**	0.57	93.59	20090	2%
Mali	MLI	**4.4**	6.56	10.76	22324	0%
Myanmar	MMR	**0.89**	0.31	3.01	26137	0%
Montenegro	MNE	**0.2**	0	0.62	0	0%
Mongolia	MNG	**2.71**	0.06	8.76	681	0%
Mozambique	MOZ	**1.61**	3	3.4	1731	0%
Mauritania	MRT	**2.79**	1.71	7.26	3407	0%
Malawi	MWI	**0.04**	0.17	0.07	44	0%
Malaysia	MYS	**0.84**	0.04	2.93	2578	0%
Namibia	NAM	**0.19**	0.18	0.78	37	0%
Niger	NER	**3.33**	5.02	6.5	5104	0%
Nigeria	NGA	**6.26**	2.93	15.17	34494	0%
Nicaragua	NIC	**0.14**	0.14	0.45	160	0%
Netherlands	NLD	**0.88**	0	1.39	34	0%
Norway	NOR	**36.84**	0	67.92	31129	0%
Nepal	NPL	**26.47**	15.52	34.38	246680	3%
New Zealand	NZL	**3.99**	0	7.89	24286	0%
Oman	OMN	**187.45**	4.18	213.03	262934	15%
Pakistan	PAK	**27.85**	21.16	23.6	5234433	9%
Panama	PAN	**0.07**	0.01	0.24	29	0%
Peru	PER	**64.02**	1.53	119.06	838953	5%

Philippines	PHL	**14.8**	0.77	34.17	1005713	3%
Poland	POL	**0.88**	0.02	1.66	898	0%
Puerto Rico	PRI	**0.1**	0	0.21	3	0%
Korea, Dem. People's Rep.	PRK	**12.25**	0.21	45.79	80948	
Portugal	PRT	**73.9**	1.15	91.79	530066	11%
Paraguay	PRY	**0.18**	0.05	0.62	335	0%
West Bank and Gaza	PSE	**102.76**	1.28	263.72	8538	1%
Qatar	QAT	**6.76**	0.96	6.76	542	0%
Romania	ROU	**1.11**	0.03	3.51	1660	0%
Russian Federation	RUS	**0.99**	0.05	2.99	18386	0%
Rwanda	RWA	**0.36**	0.09	2.58	37	0%
Saudi Arabia	SAU	**21.01**	2.31	21.74	366282	2%
Sudan	SDN	**3.91**	3.79	7.1	101409	1%
Senegal	SEN	**1.04**	3.8	0.54	2157	0%
Sierra Leone	SLE	**0.03**	0.05	0.18	1	0%
El Salvador	SLV	**0.41**	0.05	1.47	584	0%
Somalia	SOM	**2.36**	5.86	7.63	4581	
Serbia	SRB	**1.11**	0.02	3.51	732	0%
South Sudan	SSD	**1.75**	2.91	2.25	420	0%
Suriname	SUR	**0.05**	0.04	0.48	20	0%
Slovak Republic	SVK	**1.26**	0.01	2.27	40	0%
Slovenia	SVN	**0.08**	0	0.15	0	0%
Sweden	SWE	**1.27**	0	2.49	96	0%
Eswatini	SWZ	**1.64**	0.29	16.49	1644	0%
Syrian Arab Republic	SYR	**11.95**	6.48	40.9	146025	
Chad	TCD	**0.26**	0.68	0.89	173	0%
Togo	TGO	**0.03**	0.06	0.14	2	0%
Thailand	THA	**14.98**	1.27	25.98	776030	2%
Tajikistan	TJK	**96.21**	5.1	161.16	910481	53%
Turkmenistan	TKM	**37.28**	4.8	54.07	979643	20%
Timor-Leste	TLS	**0.23**	0.14	1.08	246	0%
Trinidad and Tobago	TTO	**0.23**	0.14	0.17	3	0%
Tunisia	TUN	**37.81**	1.47	55.67	139544	3%
Turkey	TUR	**162.23**	1.01	255.45	8263471	17%
Tanzania	TZA	**0.15**	0.3	0.76	712	0%
Uganda	UGA	**0.18**	0.07	1.15	47	0%
Ukraine	UKR	**4.88**	0.15	11.31	14712	0%
Uruguay	URY	**0.46**	0.05	0.88	1466	0%
United States	USA	**36.46**	0	49.22	6425522	3%
Uzbekistan	UZB	**65.81**	2.37	125.33	3577273	24%
Venezuela, RB	VEN	**20.24**	0.63	179.69	338175	1%

Vietnam	VNM	**14.47**	1.03	34.25	1122380	3%
Yemen, Rep.	YEM	**55.74**	15.86	92.53	180323	15%
South Africa	ZAF	**9.03**	2.2	39.34	102826	2%
Zambia	ZMB	**0.07**	0.16	0.32	77	0%
Zimbabwe	ZWE	**2.06**	3.43	6.95	5702	1%

Table 4: water damages sorted by malnutrition component larger than income component, total damage costs yr^{-1} in millions US$2020 PPP using annual (2019) withdrawals for agriculture, and the size of total damage costs yr^{-1} compared to annual (2019) GVA of agriculture

Country	Malnutrition costs as percentage of income loss		Country	Damage costs (millions US$2020 PPP)		Country	Percent Damage costs against GVA
Senegal	700%		India	34648		Kyrgyz Republic	60%
Malawi	245%		China	12061		Tajikistan	53%
South Sudan	130%		Turkey	8263		Greece	32%
Pakistan	90%		Japan	8177		Uzbekistan	24%
Mozambique	88%		United States	6426		Armenia	22%
Angola	85%		Iran, Islamic Rep.	5507		Turkmenistan	20%
Trinidad and Tobago	85%		Pakistan	5234		Iran, Islamic Rep.	18%
Niger	77%		Uzbekistan	3577		Turkey	17%
Somalia	77%		Spain	2513		United Arab Emirates	17%
Chad	76%		Greece	2460		Chile	16%
Mali	61%		Egypt, Arab Rep.	2077		Yemen, Rep.	15%
Djibouti	59%		Indonesia	1713		Oman	15%
Sudan	53%		Mexico	1690		Azerbaijan	14%
Zambia	50%		Chile	1649		Japan	13%
Zimbabwe	49%		Korea, Rep.	1164		Iraq	11%
Nepal	45%		Vietnam	1122		Portugal	11%
Cote d'Ivoire	44%		Philippines	1006		Kuwait	10%
Afghanistan	43%		Turkmenistan	980		Cyprus	9%
Togo	41%		Tajikistan	910		Pakistan	9%
Tanzania	39%		Peru	839		Afghanistan	8%

2.11.2 Distributions of marginal and total damage costs

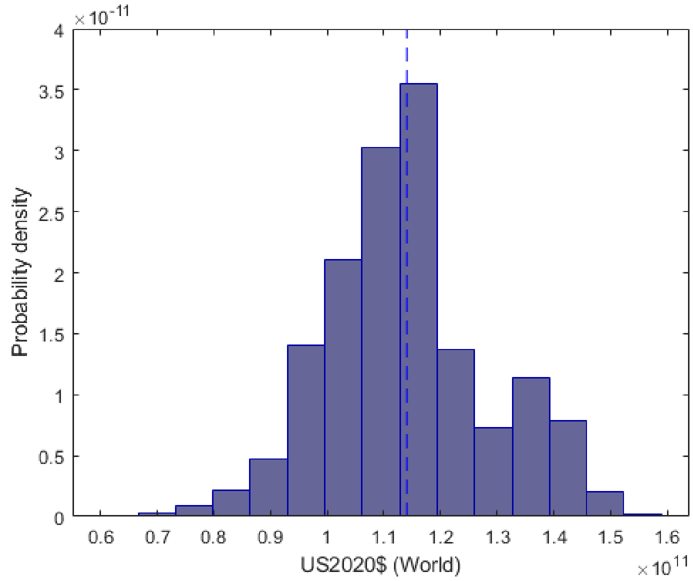
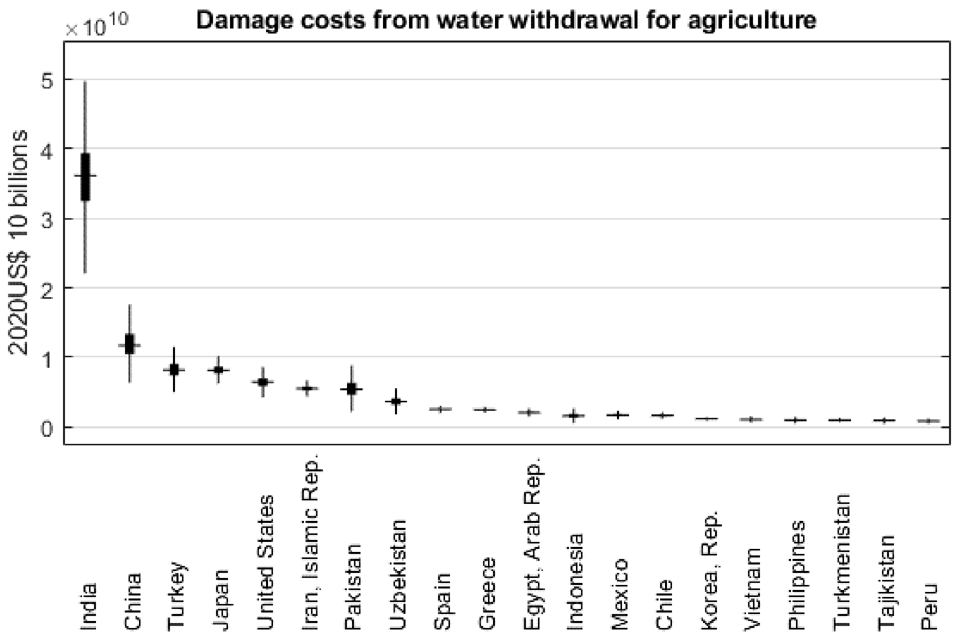


Figure 6: "Hidden" cost of water withdrawal in agriculture, obtained by summing marginal costs and total withdrawals across the 164 countries in Table 2. Derived samples and not parametric estimates used. The joint distribution of marginal damage water costs for individual countries are moderately to weakly positively correlated, resulting in a slightly skew distribution shape for the addition of many weakly correlated random variables. Expected costs of ~115 billion US$2020 PPP.



Annex A

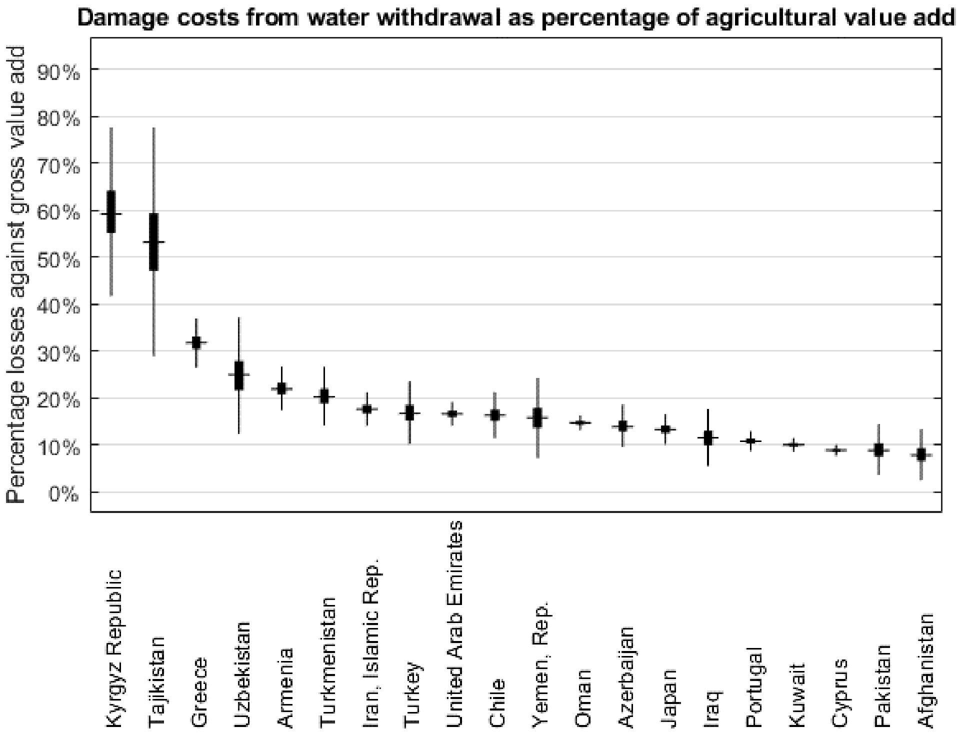


Figure 7: Highest damage costs using the quantity of agricultural water withdrawals for 2019, and a comparison of damage cost against agricultural GVA for 2019. Long cross lines in the box plot represent median values, and the thick line represents the interquartile range. Derived samples and not parametric estimates used.

Annex A

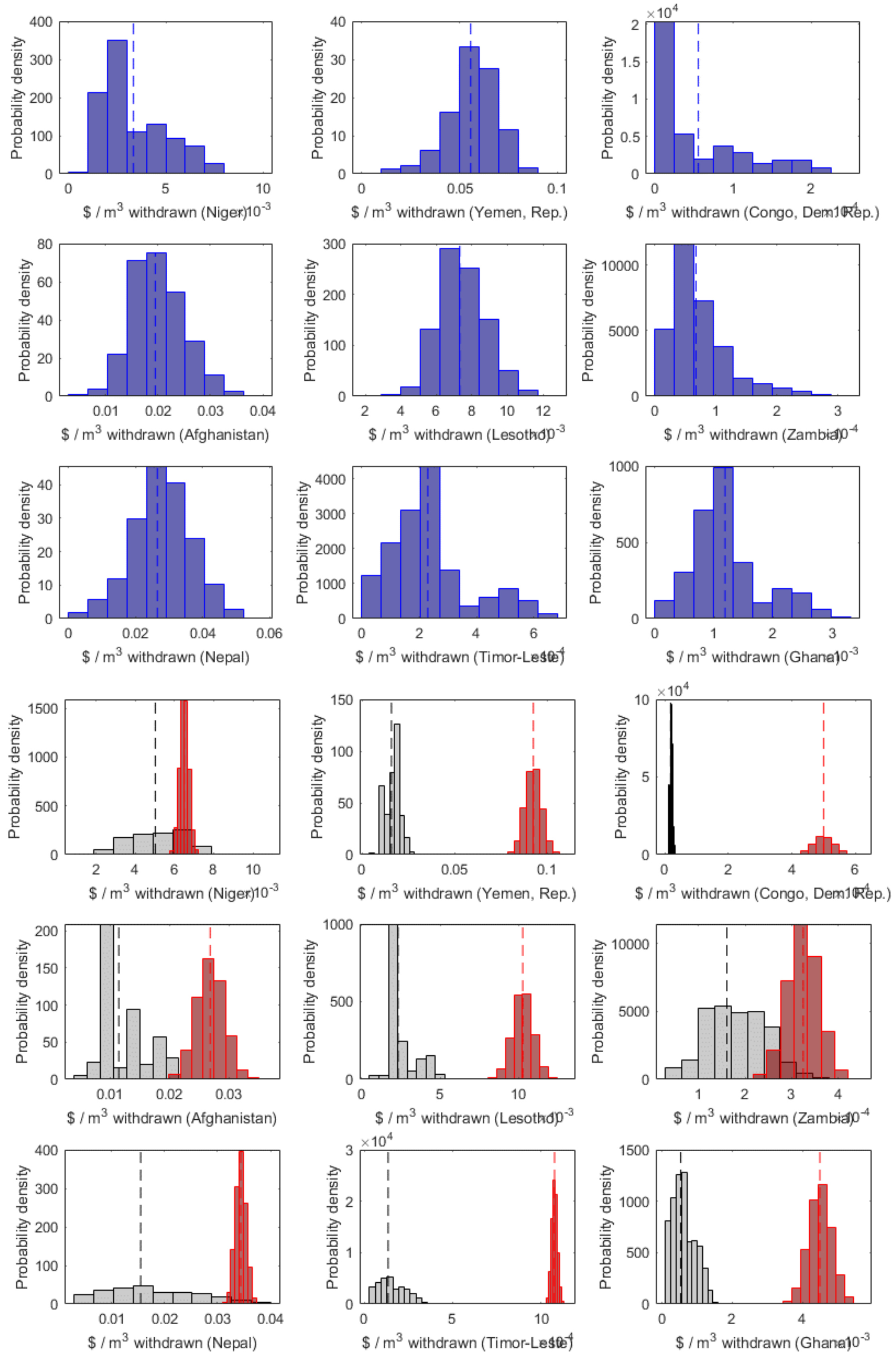


Figure 8: example distributions of samples of MDC (blue) for HDI <0.625. Malnutrition MDC_water (grey) and income damages (red) are shown separated in the bottom panel uncorrected and undiscounted.

Annex A

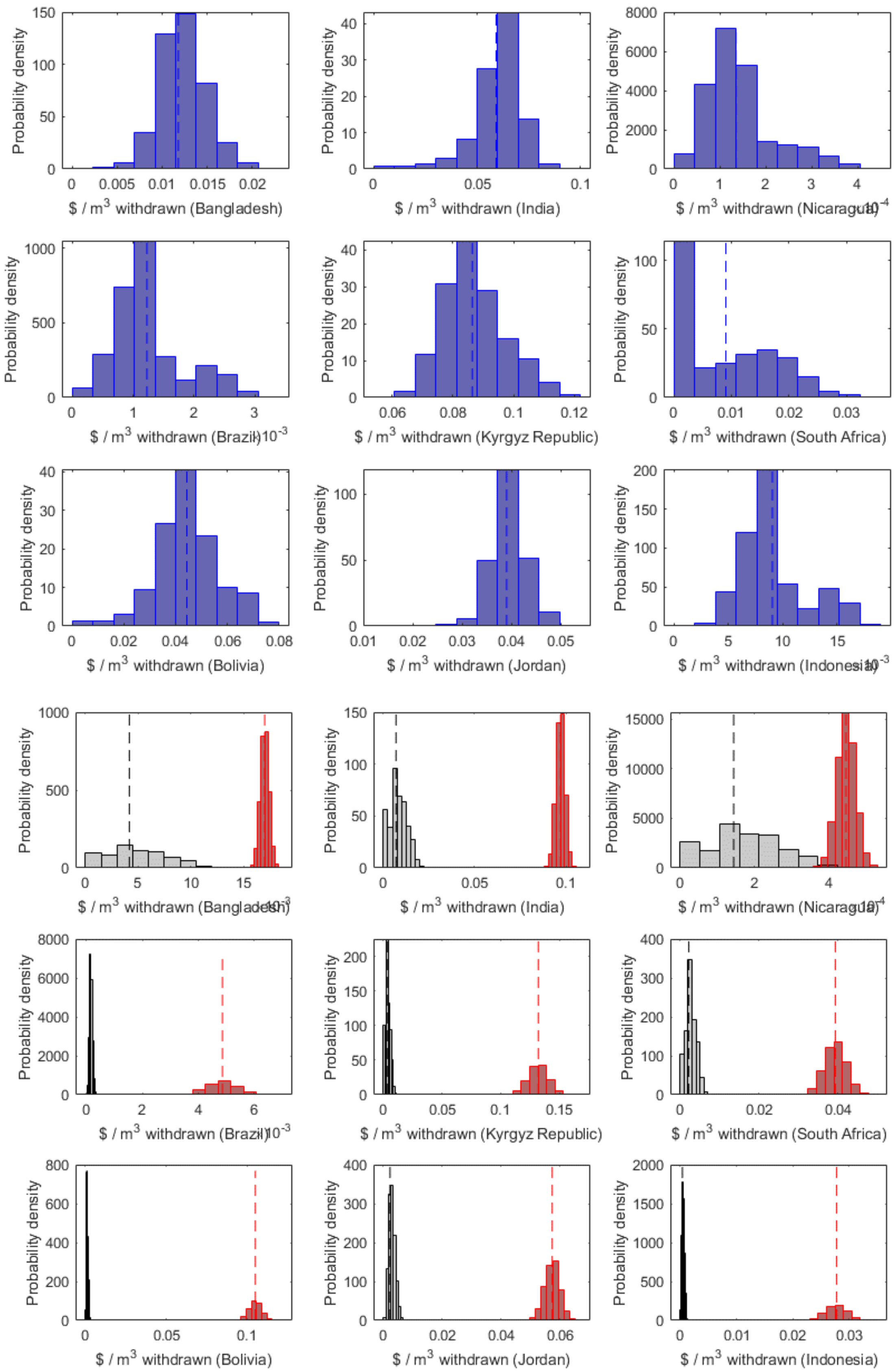


Figure 9 example distributions of samples of MDC (blue) for 0.625 < HDI <0.75. Malnutrition (grey) and income damages (red) are shown separated in the bottom panel uncorrected and undiscounted.

Annex A

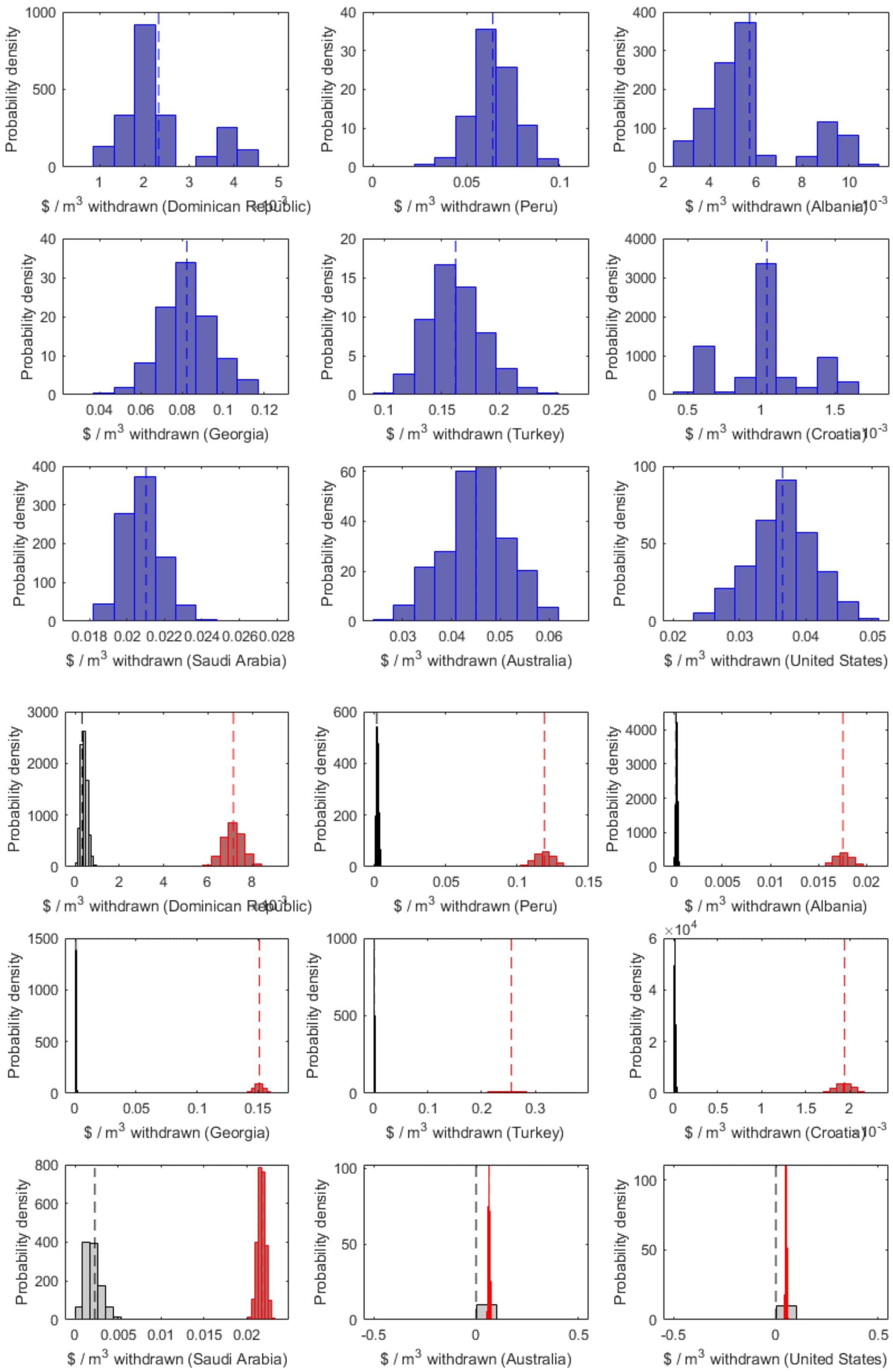


Figure 10: example distributions of samples of MDC (blue) for 0. HDI > 0.75. Malnutrition (grey) and income damages (red) are shown separated in the bottom panel uncorrected and undiscounted. Malnutrition losses are zero for HDI > 0.89.

Annex A

2.11.3 Additional figures on Bayesian regression and example distributions of components

Fit of the residuals in the OLS MLE estimate of the quadratic surface in Figure 2. A Bayesian regression was used to estimate uncertainty in the factor DF_i:

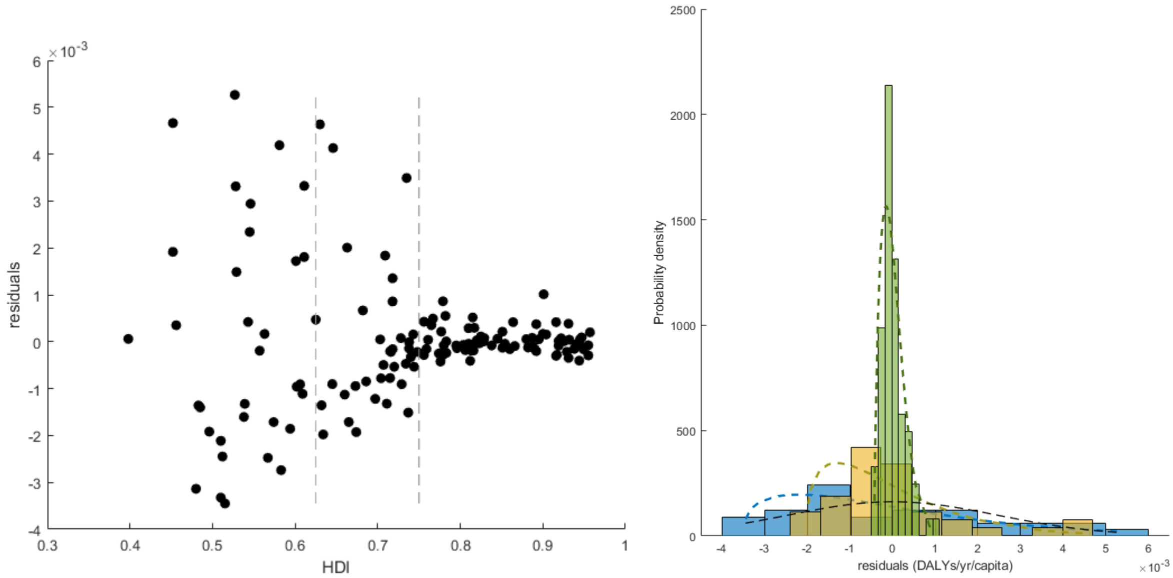


Figure 11: left panel shows heteroscedasticity in residuals for the OLS MLE quadratic surface fit. Three intervals of HDI (HDI < 0.625, 0.625<= HDI < 0.75, HDI >=0.75) were chosen for models of the residuals for a Bayesian regression on the parameter space of the quadratic fit. Right panel shows MLE fits of the residuals (Weibull distributions) in the three different intervals. HDI < 0.625 as blue, 0.625<= HDI < 0.75 is orange and HDI >= 0.75 in green. Ignoring heteroscedasticity would result in a poor MLE fit of a normal distribution to all residuals (black dashed curve).

Marginals on the joint parameter space $(\gamma_1, \gamma_2, \gamma_3)$ for the Bayesian quadratic fit of $HDF_i, 0.3 \leq HDI < 0.89$ within the factor EF_i:

$$HDF(HDI, (\gamma_1, \gamma_2, \gamma_3)) = \frac{\gamma_3 + HDI \cdot \gamma_2 + HDI^2 \cdot \gamma_1}{\gamma_3 + 0.3 \cdot \gamma_2 + 0.3^2 \cdot \gamma_1}.$$

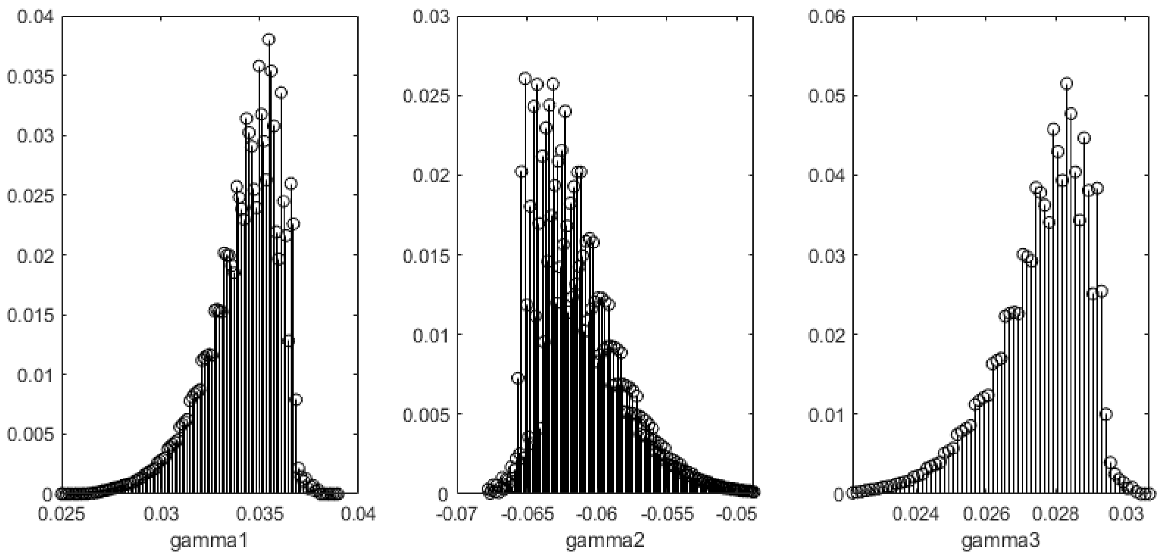


Figure 12: marginals on the joint parameter space $(\gamma_1, \gamma_2, \gamma_3)$.

Example results for the factor EF for HDI < 0.625:

Annex A

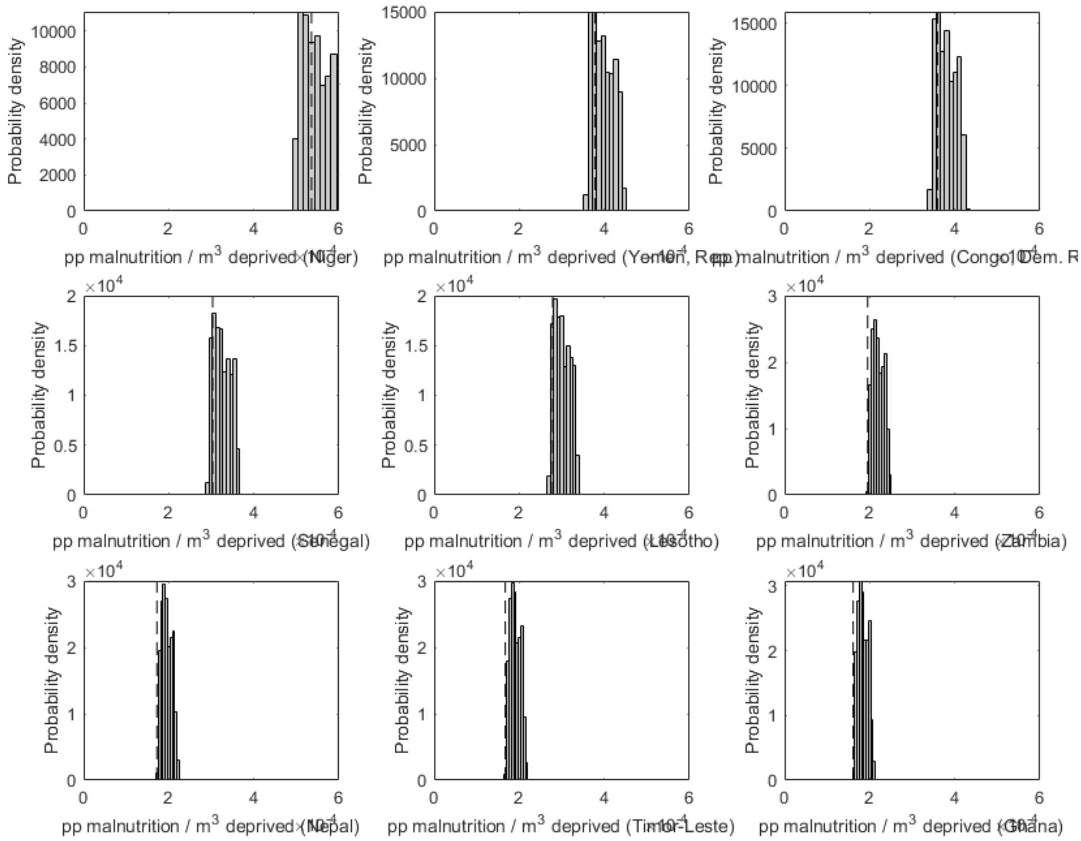


Figure 13: examples of distributions for the factor EF from equation (1). For example, in Ghana the factor derived from the method of [9] indicates 0.2 people undernourished from damage to water resources present or future per 1000 m^3 (megalitre) withdrawn for agriculture.

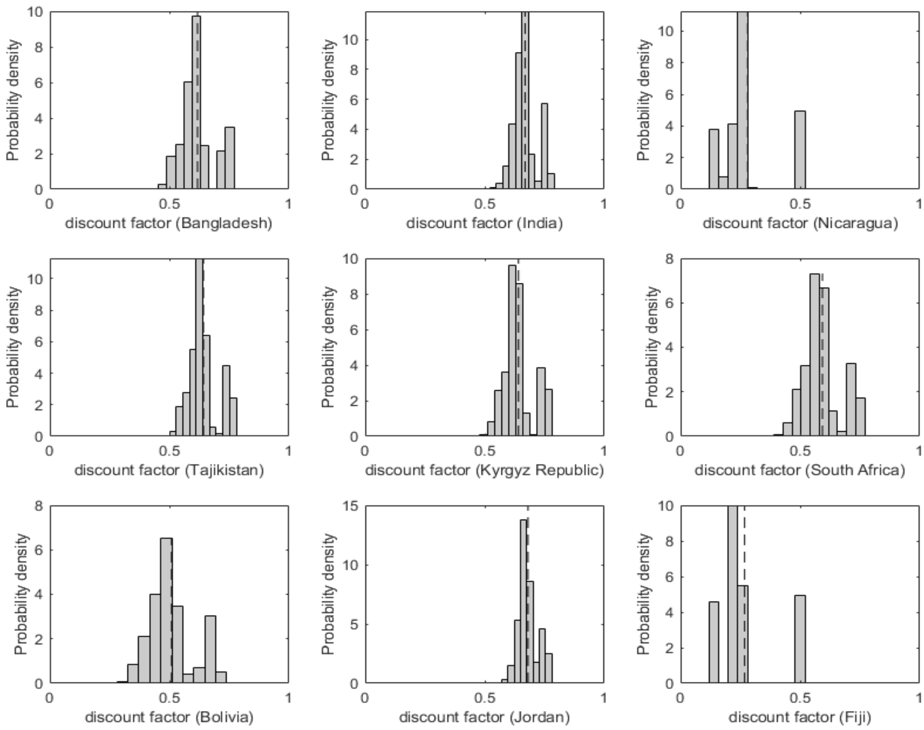


Figure 14 examples of distributions of the discount factor ρ, which depends on the water stress index. The main discrete variation is due to uncertainty in the discount rate (GDP growth) across SSPs.