ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Large variations in global irrigation withdrawals caused by uncertain irrigation efficiencies

To cite this article: Arnald Puy *et al* 2022 *Environ. Res. Lett.* **17** 044014

View the article online for updates and enhancements.

You may also like

- Growing farms and groundwater depletion in the Kansas High Plains
Yufei Z Ao, Nathan P Hendricks and Landon T Marston
- Irrigation enhances local warming with greater nocturnal warming effects than daytime cooling effects
Xing Chen and Su-Jong Jeong
- Assessment of transboundary aquifers of the world—vulnerability arising from human water use
Yoshihide Wada and Lena Heinrich

This content was downloaded from IP address 83.51.151.152 on 15/03/2022 at 11:09

ENVIRONMENTAL RESEARCH
LETTERS

OPEN ACCESS

RECEIVED
18 November 2021

REVISED
9 February 2022

ACCEPTED FOR PUBLICATION
22 February 2022

PUBLISHED
14 March 2022

Original Content from this work may be used under the terms of the Creative Commons Attribution 4.0 licence.

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

LETTER

Large variations in global irrigation withdrawals caused by uncertain irrigation efficiencies

Arnald Puy[1,2,*], **Bruce Lankford**[3], **Jonas Meier**[4], **Saskia van der Kooij**[5] **and Andrea Saltelli**[1,6]

[1] Centre for the Study of the Sciences and the Humanities (SVT), University of Bergen, Parkveien 9, PB 7805, 5020 Bergen, Norway
[2] Department of Ecology and Evolutionary Biology, Princeton University, M31 Guyot Hall, Princeton, NJ, 08544, United States of America
[3] School of International Development, University of East Anglia, Norwich NR4 7TJ, United Kingdom
[4] German Aerospace Center (DLR), German Remote Sensing Data Center (DFD), Münchner Strasse 20, 82234 Oberpfaffenhofen, Germany
[5] Water Resources Management, Department of Environmental Sciences, Wageningen University & Research, Droevendaalsesteeg 3 6708PB Wageningen, The Netherlands
[6] Institute for Cognitive Sciences and Technologies of the Italian National Research Council (CNR), Via S. Martino della Battaglia 44, 00185 Roma, Italy
[*] Author to whom any correspondence should be addressed.

E-mail: arnald.puy@uib.no **and** apuy@princeton.edu

Keywords: sensitivity analysis, agriculture, water sustainability, climate change

Supplementary material for this article is available online

Abstract

An assessment of the human impact on the global water cycle requires estimating the volume of water withdrawn for irrigated agriculture. A key parameter in this calculation is the irrigation efficiency, which corrects for the fraction of water lost between irrigation withdrawals and the crop due to management, distribution or conveyance losses. Here we show that the irrigation efficiency used in global irrigation models is flawed for it overlooks key ambiguities in partial efficiencies, irrigation technologies, the definition of 'large-scale' irrigated areas or managerial factors. Once accounted for, these uncertainties can make irrigation withdrawal estimates fluctuate by more than one order of magnitude at the country level. Such variability is larger and leads to more extreme values than that caused by the uncertainties related with climate change. Our results highlight the need to embrace deep uncertainties in irrigation efficiency to prevent the design of shortsighted policies at the river basin-water-agricultural interface.

1. Introduction

Managing water withdrawals within water allocation balances desirable sustainable goals of attaining food and water security, boosting human health, fostering economic growth, protecting freshwater ecology and reducing conflict over water [1, 2]. Central to this task of apportionment is knowledge of the large volumes of water withdrawn by irrigation, which informs discussions on whether global water availability can ensure future food production [3] and whether we can safely reallocate water from irrigation to other sectors [4]. Such knowledge is also key to related water management tasks such as determining water basin accounts [5], planning water storage and abstraction infrastructure [6], finding areas of untapped potential [7], managing licensed abstractions on rivers or apportioning limited water within specific drought events [8]. Climate change will further exacerbate the scale of these withdrawals and allocation challenges by increasing the variability of precipitation and boosting crop water needs due to higher temperatures and evapotranspiration [9, 10].

These ever-sharpening water tasks require increasingly accurate knowledge of withdrawn water at the irrigation system, basin, country and global levels. At the core of this knowledge there is the concept of irrigation efficiency [11, 12], which helps to transform net crop-level consumption into water needs for the irrigation system, giving by extension water withdrawals at the basin and global levels. In its classical form [13, 14], the concept of irrigation efficiency denotes the ratio of irrigation water beneficially consumed by the crop to that diverted from the water source and conveyed to the crop. The closer

© 2022 The Author(s). Published by IOP Publishing Ltd

this ratio is to 1, the higher the irrigation efficiency of the irrigated area under study.

Although continuously alterable via design, operation and management, irrigation efficiency is often characterized with the static, sharp point-estimates proposed by irrigation engineers more than 50 years ago [15, 16]. This is especially the case of global models (GMs) [17–22], spatially distributed algorithms that simulate hydrological processes at a global scale. For instance, WaterGap [23], H08 [18] or MATSIRO [17] characterize the irrigation efficiency of USA with a value of 0.6 [23], whereas PCR-GLOBWB [24] or LPJmL [25] use a value of 0.55 [26]. All these GMs have gained momentum over the last 20 years and their water estimates currently feed into the World Water Development Reports, the Global Environmental Outlooks or studies commissioned by the World Bank [27]. They are also regarded as paramount when discussing the sustainable development goals (SDGs) at the Water-Food nexus given their capacity to simulate connections between crops, water and humans over large spatial and temporal scales [28].

Here we provide a comprehensive analysis of the theoretical and empirical foundations of the irrigation efficiency values used by GMs to simulate irrigation water withdrawals. By means of a literature review, sensitivity auditing and uncertainty analysis methods [29, 30], we show that they endorse a vision of irrigation that artificially downplays ambiguities and reduces real-world complexity to a set of easy-to-manage numbers. Once this spurious accuracy is corrected for, irrigation efficiencies used by GMs turn from point-estimates to ranges that can span almost all the unit interval. Such variability engulfs the estimation of irrigation water withdrawals with an uncertainty much larger than that propagated by the uncertainties derived from climate change. Our results thus show how a relatively obscure step in irrigation planning (irrigation efficiency) governs estimates of, and discussions regarding, globally significant water balances, and concur with recent works suggesting that GMs promote tunnel vision in the irrigation policy field [31, 32]. This can potentially misguide initiatives on the sectoral allocation of water out of agriculture [4], the planning for dams [33]; the viability of groundwater storage [34] or the pursuit of the SDGs [2]. We conclude by discussing the role that GMs should play in informing sustainable policies at the water-agricultural interface.

2. Methods

2.1. Sensitivity auditing

Two main studies provide GMs with irrigation efficiency values: Döll and Siebert [23] (utilized by MATSIRO, H08, WaterGap and WBM_{plus} [17–20]) and Rohwer *et al* [26] (used by LPJmL and PCR-GLOBWB [21, 22, 35, 36]). Döll and Siebert's are regional estimates based on a literature survey, whereas Rohwer *et al*'s are country-level estimates modeled as a function of partial efficiencies (field, conveyance and management efficiencies) and irrigation technologies (surface, sprinkler and micro-irrigation). GMs use the values proposed by either Döll and Siebert or Rohwer *et al* to transform country or region-based crop water needs into irrigation water withdrawals.

We cross-check the estimates by Döll and Siebert [23] and Rohwer *et al* [26] against the studies they cite to support their proposed irrigation efficiency values [15, 16, 37–42]. Our goal is twofold:

- To highlight the assumptions embedded in the calculation of irrigation efficiency. We rely on sensitivity auditing [29], an extension of sensitivity analysis to gauge the framing of mathematical models. Sensitivity auditing investigates the value-ladenness of key assumptions and normative frameworks of models. This is achieved by hunting for tacit or neglected assumptions, strategic minimizations of uncertainties and normative stances underlying the framing of the problem. Such scrutiny increases the transparency of model-based inferences and helps assessing their social robustness for policy-making. The use of sensitivity auditing is recommended in the new guidelines for impact assessment issued by the European Commission [43].
- To extract numerical data to describe the uncertainty in the parameters used to calculate irrigation efficiency [16, 26, 37] (see section 2.4).

2.2. Data collection from ISI-MIP

We retrieve irrigation water withdrawal estimates from WaterGap [19], H08 [44], PCR-GLOBWB [45] and LPJmL [25] in the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) [46]. In ISI-MIP all these GMs assume an irrigation efficiency of 1 except LPJmL, whose irrigation efficiencies vary spatially. To make all estimates comparable, we correct the irrigation water withdrawal values produced by LPJmL following the indications given by ISI-MIP [47].

All these models have a spatial resolution of $0.5^{\circ} \times 0.5^{\circ}$ and compute irrigation water withdrawals at the grid cell level. We retrieve data from 2010 at a monthly time step and allocate each cell to a country according to its coordinates. We produce annual irrigation water withdrawal estimates by adding all the values of all cells within the same country. We also retrieve from ISI-MIP the water withdrawal estimates projected by these models for 2050 under four different Representative Concentration Pathways (RCP2.6, RCP4.5, RCP6, RCP8.5). We aim to examine whether the preferential attention given in the literature to uncertainties related to climate change versus those related to irrigation efficiency appears justified [48, 49].

2.3. The model

Irrigation efficiency (E_p) [-] is a key parameter to compute irrigation water withdrawals (I_w) [m^3], since

$$I_w = \frac{I_c}{E_p}, \tag{1}$$

where I_c [m^3] is the water needed by the crop due to transpiration, evapotranspiration and evaporation from the soil surface. Hence $\lim_{E_p \to 1} I_c = I_w$. To calculate E_p we use the classical approach based on partial efficiencies [16, 37, 50], also employed by Rohwer *et al* [26] and sanctioned by GMs, which reads as

$$E_p = E_a E_c M_f, \tag{2}$$

where E_a [-] is the field efficiency, E_c [-] is the conveyance efficiency and M_f [-] is a management factor defined by Rohwer *et al* [26] as

$$M_f = \begin{cases} m & \text{for sprinkler and micro-irrigation} \\ m - r_L f_L & \text{for surface irrigation} \end{cases} \tag{3}$$

where m [-] is a management parameter, r_L [-] denotes the reduction in management efficiency in large-scale irrigated areas and f_L [-] designates the fraction of large-scale irrigated areas. Note that Rohwer *et al* [26] assume the existence of a management penalization due to scalar stress only in large-scale surface irrigation systems (equation (3)), which they define as those larger than 10 000 ha based on the Global Map of Irrigated Areas (FAO-GMIA [51]). The final E_p is in the interval $[0, 1]$, with higher irrigation efficiencies showing values closer to 1.

Rohwer *et al* [26] calculated irrigation efficiency based on the 'predominant' technology in the country due to the sparcity of data on the specific proportion of flood, sprinkler and micro-irrigation at the national level. These data were recently produced by Jägermeyr *et al* [25]. To see whether the addition of spatial detail in the distribution of irrigation technologies improves the accuracy of the estimation, we also calculate the irrigation efficiency with the Jägermeyr *et al* [25] coefficients, as

$$E_p = C_s E_{p_s} + C_p E_{p_p} + C_m E_{p_m}, \tag{4}$$

where E_{p_s}, E_{p_p} and E_{p_m} respectively denote the irrigation efficiency of surface, sprinkler and micro-irrigation (calculated as in equation (2)) and C_s, C_p and C_m are constants denoting the fraction of irrigated area with surface, sprinkler and micro-irrigation as reported by Jägermeyr *et al* [25].

Note that equations (2) and (4) are different versions of the method known as the 'factorial' approach to irrigation efficiency. This method offers a single snap-shot of irrigation efficiency by multiplying different tiers of irrigation together (three in this case), which makes it very sensitive to errors or changes in the values of these tiers. The limitations of the factorial approach are thoroughly discussed in Lankford [52].

2.4. Probability distributions

We describe the uncertainty in the parameters of equations (2) and (3) with probability distributions based on the literature review outlined in the section 2.1 (table 1). We model E_a and E_c for surface and sprinkler irrigation based on Bos and Nugteren [37], and E_a and E_c for micro-irrigation according to the ranges reported by Fairweather *et al* [41], Brouwer *et al* [16] and Rohwer *et al* [26]. With regards to *Mf*, we assume that m tends to 1 but that mismanagement and bad communication can eventually bring m down to 0.65, thus reducing the efficiency as proposed by Doorenbos and Pruitt [15]. For the parameter r_L we set the upper bound at 0.5 following Rohwer *et al* [26] and assume that its lower bound may be zero given the existence of large irrigated areas successfully managed through time, such as the *huerta* of València or Murcia (Spain) [53].

Finally, we operationalize f_L with two triggers (X_1, X_2), e.g. random parameters that account for the uncertainty in two key aspects related with the characterization of 'large-scale' irrigated areas: the dataset used to document the extension of irrigation and the threshold size used to define 'large-scale' irrigated areas. Although Rohwer *et al* use the FAO-GMIA and 10 000 ha respectively, there are currently four different datasets informing on the extension of irrigation [51, 54, 55], and no clear agreement as to what 'large-scale' irrigated areas are [56]. We thus employ X_1 to select one of these four irrigated area datasets and X_2 to define the threshold size beyond which irrigated areas are considered 'large-scale' (see section 2.5). This design results in ten uncertain parameters/triggers (table 1).

2.5. 'Large-scale' irrigated areas

We consider four irrigation maps to characterize X_1: the FAO-GMIA [57], the IWMI-GIAM [55], the GRIPC [58] and the map by Meier *et al* [54]. The FAO-GMIA is based on spatially aggregated official statistics and reports irrigated areas relative to the total grid cell area. The IWMI-GIAM defines irrigated areas depending on the crop class, whereas the GRIPC and the Meier *et al* map provide a binary irrigation mask. To remain consistent with Rohwer *et al* [26], we adjust all datasets to the FAO-GMIA and determine the percentage of irrigated area in each grid cell. We identify 'large-scale' irrigated areas as contiguous grid cells with >50% irrigation coverage and a total irrigated area $> p$, where p is the uncertain threshold size operationalized by X_2. We focus on $p = 1000$ ha, $p = 3000$ ha and $p = 10\,000$ ha. We could not explore $p < 1000$ ha given the need for >50% irrigation coverage and the spatial resolution of the dataset.

Table 1. Probability distributions used to describe the uncertainty in the parameters involved in the estimation of irrigation efficiency. *TWei*, *TBeta* and $\mathcal{DU}$ stand for truncated Weibull, truncated Beta and discrete univariate respectively. See figure S1 for a graphical representation of the selected probability distributions.

Parameter	Description	Distribution
$E_{a_{su}}$	Field efficiency surface irrigation	$TWei(3.5, 0.5, 0.14, 0.87)$
$E_{a_{sp}}$	Field efficiency sprinkler irrigation	$TWei(6.99, 0.74, 0.49, 0.88)$
$E_{a_{mi}}$	Field efficiency micro-irrigation	$\mathcal{U}(0.75, 0.9)$
$E_{c_{su}}$	Conveyance efficiency surface irrigation	$TBeta(5.75, 1.4, 0.26, 0.98)$
$E_{c_{sp}}$	Conveyance efficiency sprinkler irrigation	$\mathcal{U}(0.64, 0.96)$
$E_{c_{mi}}$	Conveyance efficiency micro-irrigation	$\mathcal{U}(0.9, 0.95)$
m	Management irrigation	$TBeta(5.75, 1.4, 0.65, 1)$
r_L	Reduction in efficiency due to mismanagement in large-scale irrigation	$\mathcal{U}(0, 0.5)$
X_1	Irrigated area dataset	$\mathcal{DU}(1, 2, 3, 4)$
X_2	Threshold size for large-scale irrigation	$\mathcal{DU}(1000, 3000, 10\,000)$

2.6. Uncertainty analysis

To appraise how these ambiguities affect the calculation of irrigation efficiency, we conduct a Monte Carlo-based uncertainty analysis with the R package `sensobol` [59]. We first create a sample matrix with $N = 2^{14}$ rows and $k = 10$ columns using Sobol' quasi-random numbers [60, 61]. The Sobol' sequence is a base-2 sequence that explores the uncertainty space more effectively than random numbers, for it leaves smaller unexplored volumes. We allocate each column in the matrix to one of the ten uncertain parameters/triggers listed in table 1, and use a quantile transformation to bring the values populating each column to its appropriate probability distribution. Any point in this matrix can be designated as x_{vi}, where v indexes the row (from 1 to N) and i indexes the column (from 1 to k). We then run the model: for $v = 1, 2, \ldots, N$ rows, we calculate the country-level irrigation efficiency E_{p_v} based on the values defined by E_{a_v}, E_{c_v}, ... following equations (2) and (3). This design allows the same set of simulations to be used also for sensitivity analysis, which helps pinpoint which parameters/triggers convey the most uncertainty to the model output [30, 62]. Due to space constraints, we provide the results of the sensitivity analysis in the supplementary materials (available online at stacks.iop.org/ERL/17/044014/mmedia).

3. Results

3.1. Large variability in irrigation efficiencies

At the regional level, the irrigation efficiency point-estimates used by GMs hide wide ranges. This is the case of the United States, whose assigned irrigation efficiency value (0.6) contrasts with the data compiled by Solley *et al* [40] at the state level (figure 1(a)). The values allocated to South (0.35), East (0.35) and South-East (0.4) Asia also tie in poorly with the estimates by Guera *et al* [39] for Indonesia (0.4–0.65), Malaysia (0.35–0.45), Thailand (0.37–0.62) and India (0.3–0.38). For the latter, Bos and Nugteren [37] report a much larger interval of efficiency values (0.14–0.4). The same applies to the efficiency apportioned by GMs to North (0.7), West (0.55), East (0.45) and South (0.45) Africa, which significantly shrink the range reported by FAO [38] for the continent (figure 1(b)). In some cases, the estimates do not seem to fall within the interval formed by the irrigation efficiency of countries within the region. This is the case of the Middle East (0.6), whose irrigation efficiency falls outside the range formed by the values of Egypt (0.3), Turkey (0.15) and Iran (0.29) reported by Bos and Nugteren [37]. We provide a detailed comparison between the point-estimates used by GMs at the regional level and the underlying irrigation efficiency data in table S1.

3.2. Irrigation technologies do not have sharp, distinguishable efficiencies

The efficiency ladder in GMs is framed as surface < sprinkler < micro-irrigation, with each technological category unequivocally improving on the previous one in both field (E_a) and conveyance (E_c) efficiency. Micro-irrigation is positioned at the summit with almost perfect values ($E_a = 0.9$, $E_c = 0.95$) (table S2). This narrative sanctions an engineering perspective of irrigation in which technologies have essential features and perform independently from social-ecological particularities and farming practices. Yet data reported at the project level indicates largely overlapping, variable partial efficiencies for surface and sprinkler irrigation [37] (figure 1(c)). The irrigation efficiency of surface, sprinkler and micro-irrigation are also reported as intervals laying considerably one over the other by Clemmens and Molden [63], Rogers *et al* [42] and Fairweather *et al* [41].

3.3. What are 'large-scale' irrigated areas?

By using Rohwer *et al*'s data [26], many GMs assume that 'large-scale' irrigated areas have lower efficiencies due to mismanagement problems and scalar stress, penalizing the irrigation efficiency of irrigated areas larger than 10 000 ha [21, 26, 36]. In figure 1(d) we show that there may not be any difference in application (E_a) or conveyance (E_c) efficiency between irrigated areas below and beyond 10 000 ha, whereas

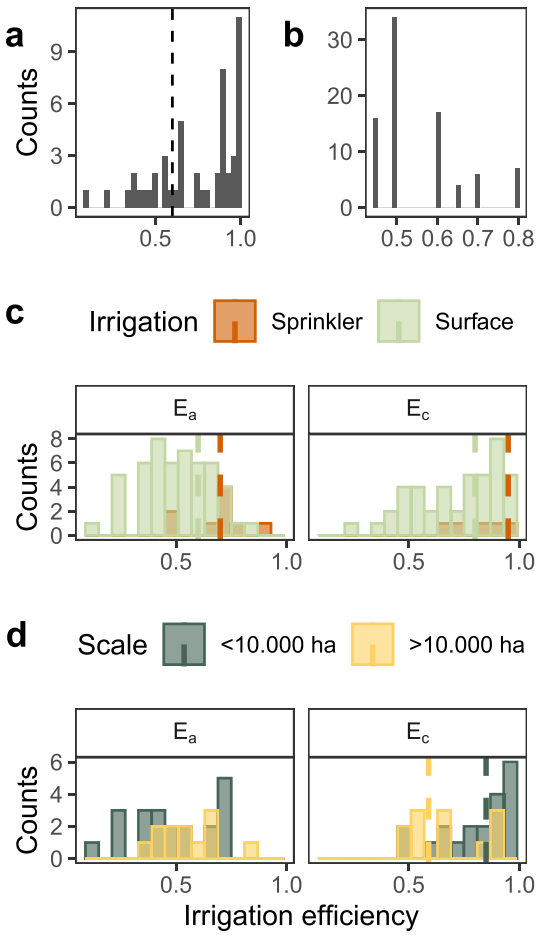

Figure 1. Comparison between the irrigation efficiency estimates used in GMs and the underlying data. (a) Distribution of efficiencies in USA according to Solley *et al* [40], calculated as consumptive water use/total water withdrawal. The vertical dashed line is the value assigned to USA by Rohwer *et al* and used by some GMs [17–20]. (b) Distribution of project efficiencies for Africa as reported by FAO [38]. (c) Distribution of field (E_a) and conveyance (E_c) efficiencies in surface and sprinkler irrigation according to Bos and Nugteren [37]. 'Surface' irrigation includes furrow, basin and border irrigation systems. The dashed vertical lines mark the point estimates defined by Rohwer *et al* and utilized by some GMs [21, 22, 35, 36]. (d) Partial efficiencies for irrigated areas below and beyond 10 000 ha according to the data compiled by Bos and Nugteren [37]. The dashed vertical lines mark the point estimates proposed by Rohwer *et al* [21, 22, 35, 36]. We have been unable to retrieve the point-estimates that Rohwer *et al* use to describe E_a.

in table S3 we report some alternative thresholds utilized in different countries to screen'large' from 'small' irrigation systems based on size (e.g. 100 ha, 1000 ha, 3000 ha). The case of Nepal is paradigmatic since the physical threshold varies one order of magnitude depending on the location of the irrigated area (flat areas: small $<$ 500 ha, large $>$ 5.000 ha; non-flat areas: small $<$ 50 ha, large $>$ 500 ha) [64].

3.4. Quantitative uncertainties

If we propagate all these uncertainties in the calculation of irrigation efficiency we obtain large irrigation efficiency ranges at the country level. We also observe that the accuracy of the estimation is not improved by refining the share occupied by flood, sprinkler and micro-irrigation: the median overlap between the density areas obtained with the Rohwer *et al* and the Jägermeyr *et al* approach is 90% for Asian and African countries, 85% for American countries and 80% for European countries (figures 2 and 3, S2). The presence of contrasting density areas for countries such as Botswana, South Africa, Oman, Mongolia, Canada or Spain is explained by a mismatch between what Rohwer *et al* identify as the most predominant technology and the share assigned to that technology by Jägermeyr *et al*: if the weight of sprinkler/micro-irrigation is high (or low) in a country classified by Rohwer *et al* into the surface (or micro) irrigation category, the irrigation efficiency values produced under the Jägermeyr *et al* approach will tend to be higher (or lower). For these countries, the selection of either a fine or a coarse-grained approach in mapping irrigation technologies already is a significant source of uncertainty in the production of irrigation efficiency estimates.

The sharp and contrasting efficiency values assigned by GMs to surface, sprinkler and micro-irrigation do not stand once uncertainties are thoroughly accounted for (figures S3 and S4). We observe a 40%–50% overlap between the efficiency of surface and mixed irrigation, a 50% overlap between sprinkler and mixed irrigation and a 30% overlap between sprinkler and surface irrigation regardless of the continent under study. In Asia, the overlap between micro and mixed irrigation is of 8% (figures S5 and S6). Overall, the irrigation efficiency ranges produced with the uncertainty analysis for surface, sprinkler and micro irrigation are much larger than those previously reported, and include much lower values (figure 4). This is explained by the factorial approach to irrigation efficiency sanctioned by GMs, which is based on the multiplication of partial efficiencies [52] (Methods, equation (2)). Very low irrigation efficiency values may be produced when partial efficiencies are characterized with values at the lower end of their distribution. For instance, an irrigation efficiency of 0.1 for surface irrigation is feasible with the factorial approach given that the uncertainty ranges for E_a, E_c and M_f include the values 0.4, 0.5 and 0.5 respectively, and thus $0.4 \times 0.5 \times 0.5 = 0.1$.

All countries except Cyprus, the United Arab Emirates and Israel ($\sim$0.48) display uncertainty ranges in irrigation efficiency larger than 0.5, with countries such as Somalia, Colombia, Serbia or Bolivia showing the largest ranges ($\sim$0.78). Many of the top countries in irrigation water withdrawals (e.g. China, India, Iran, Spain) show uncertainty ranges larger than 0.6 (figure S7). If we let the irrigation efficiency values fluctuate within the uncertainty bounds just computed, the irrigation water withdrawals of these countries may vary by up to a factor of 50. Overall, the uncertainty in irrigation efficiency makes the irrigation water withdrawal estimates of 25%, 50%,

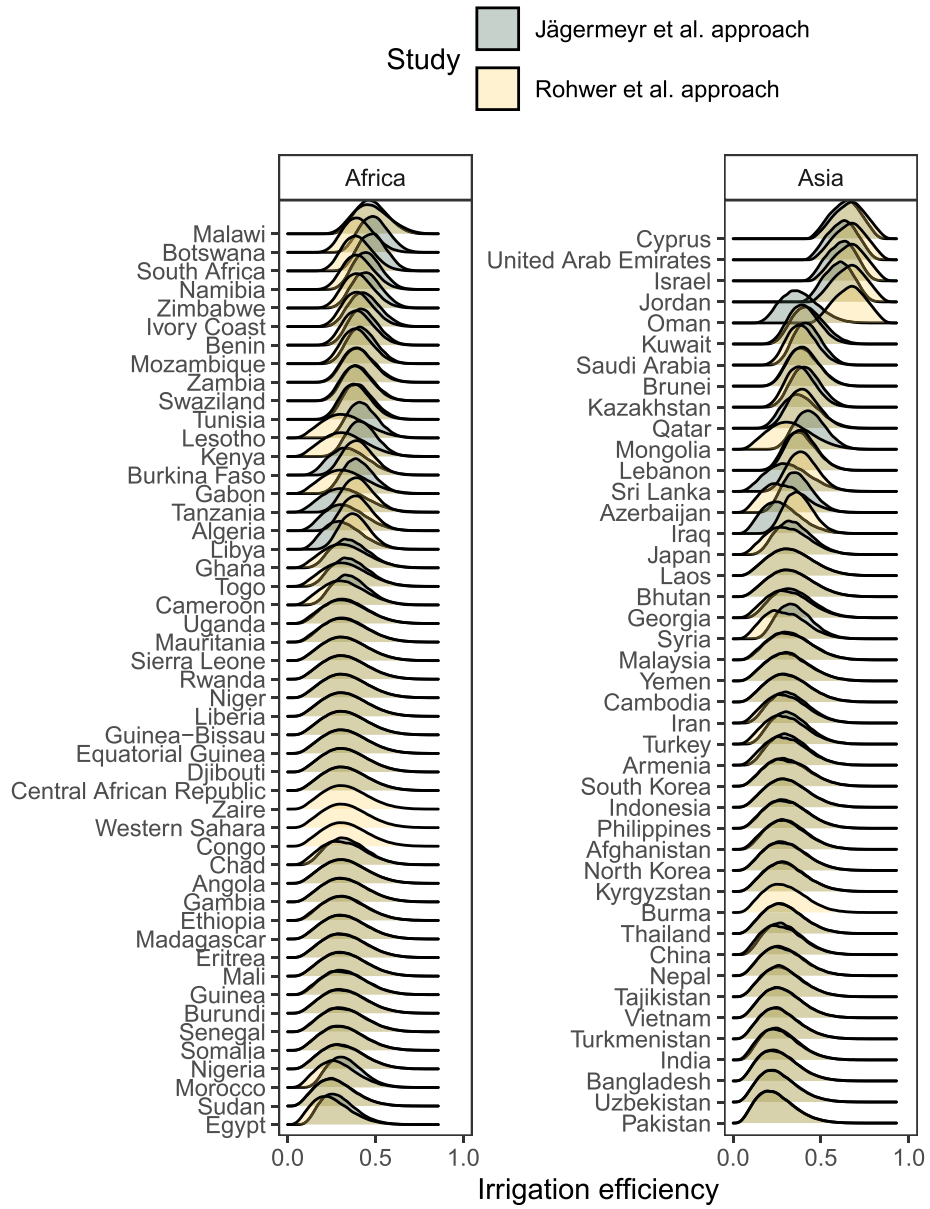

Figure 2. Comparison between the uncertainty in the irrigation efficiency of African and Asian countries under two different assumptions: (a) the share occupied by surface, sprinkler and micro-irrigation is known (Jägermeyr *et al* approach, equation (4)), and (b) the share occupied by surface, sprinkler and micro-irrigation is not known (Rohwer *et al* approach, equation (2)).

75% and 97.5% of the countries vary by up to a factor of 4, 19, 25 and 32 respectively. The countries placed at the top 2.5% of this distribution present values that can vary by up to a factor of 48 (figure S8).

Uncertainties in irrigation efficiency have a much larger effect on the estimation of irrigation water withdrawals than those derived from climate change (figure 5). In the case of India, potential water withdrawals range from 400 to 800 10^9 m^3 under climate change and from 400 to 7000 10^9 m^3 if irrigation efficiency uncertainties are accounted for ($q_{2.5}$–$q_{97.5}$). A similar situation occurs for Mexico (40–70 10^9 m^3 under climate change; 90–500 10^9 m^3 under irrigation efficiency uncertainties), Egypt (50–180 10^9 m^3; 60–1300 10^9 m^3) or Spain (20–60 10^9 m^3; 30–170 10^9 m^3) ($q_{2.5}$–$q_{97.5}$). Note how the integration of irrigation efficiency uncertainties makes Egypt and India produce irrigation water withdrawal values that extend out of scale, i.e. that are beyond the estimates projected by GMs at the global level for 2050 (3000–5000 10^9 m^3). This illustrates the extent to which current calculations of irrigation water withdrawals are constrained by arbitrarily precise irrigation efficiency values.

For 75% of the countries, the highest irrigation water withdrawal value produced after integrating irrigation efficiency uncertainties is at least two times higher than the highest value produced under climate change. For example, countries such as Bhutan, Guyana, Cameroon or Indonesia present values that are 100, 30, 20 and 17 times higher respectively. Only ten countries out of 143 (6%) (e.g. Benin,

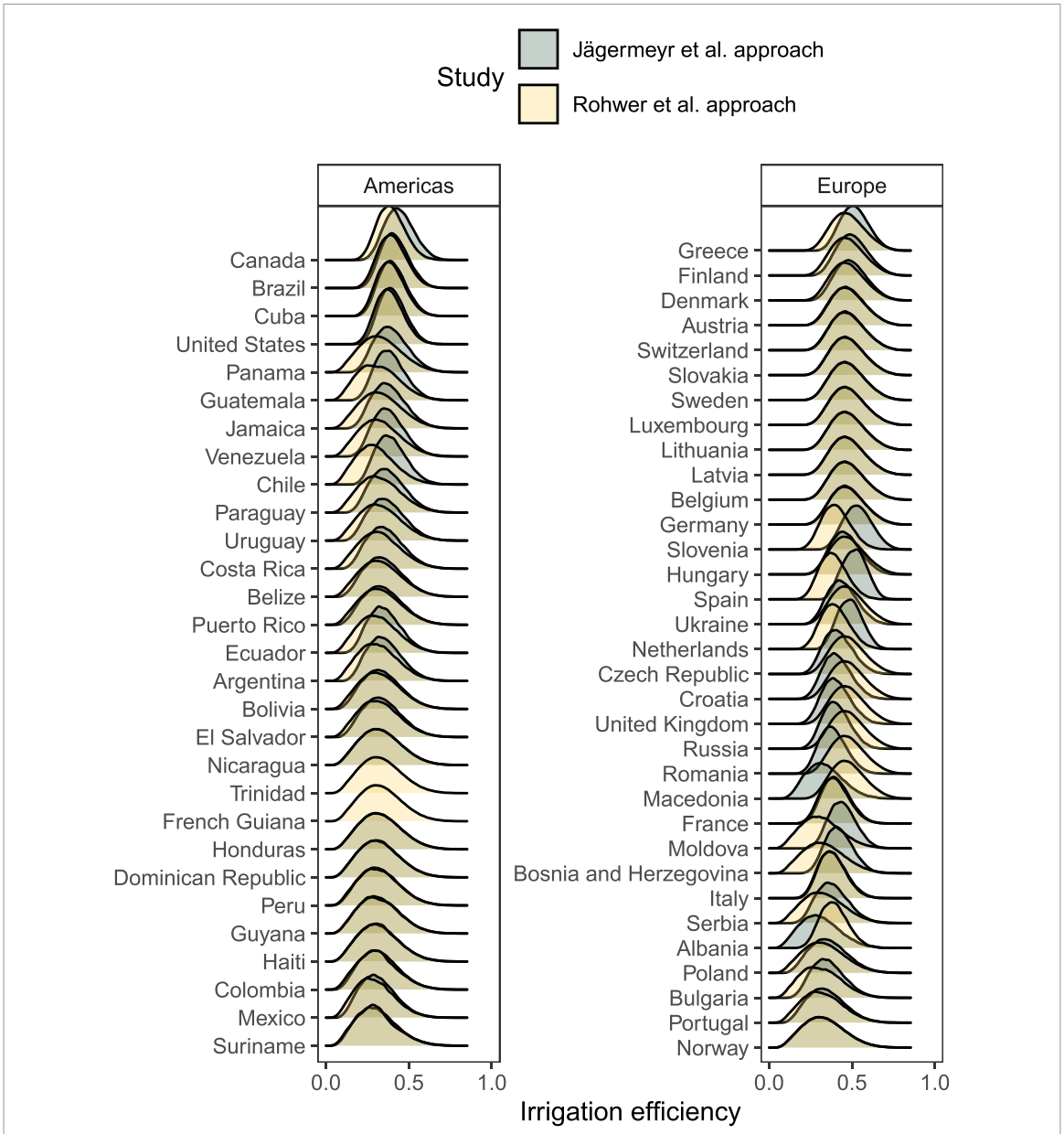

Figure 3. Comparison between the uncertainty in the irrigation efficiency of American and European countries under two different assumptions: (a) the share occupied by surface, sprinkler and micro-irrigation is known (Jägermeyr *et al* approach, equation (4)), and (b) the share occupied by surface, sprinkler and micro-irrigation is not known (Rohwer *et al* approach, equation (2)).

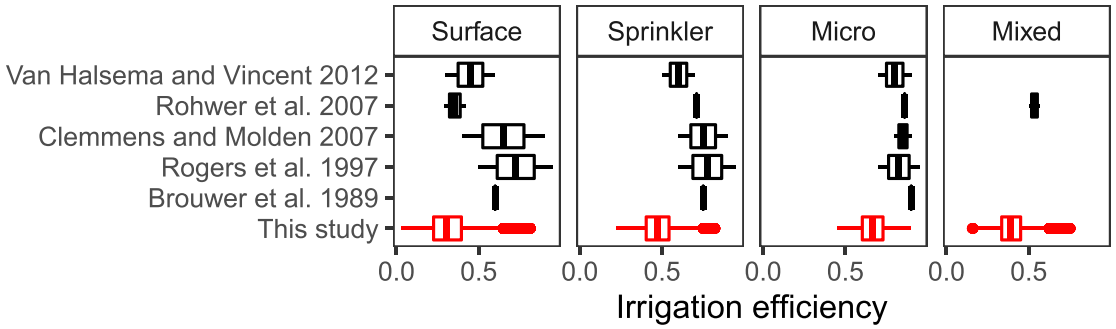

Figure 4. Boxplots displaying the values in irrigation efficiency proposed by Rohwer *et al* [26], Clemmens and Molden [63], Rogers *et al* [42], Van Halsema and Vincent [11] and Brouwer *et al* [16] and those produced in this study (in red) (center line, median; box limits, upper and lower quartiles; whiskers, 1.5x interquartile range; points, outliers).

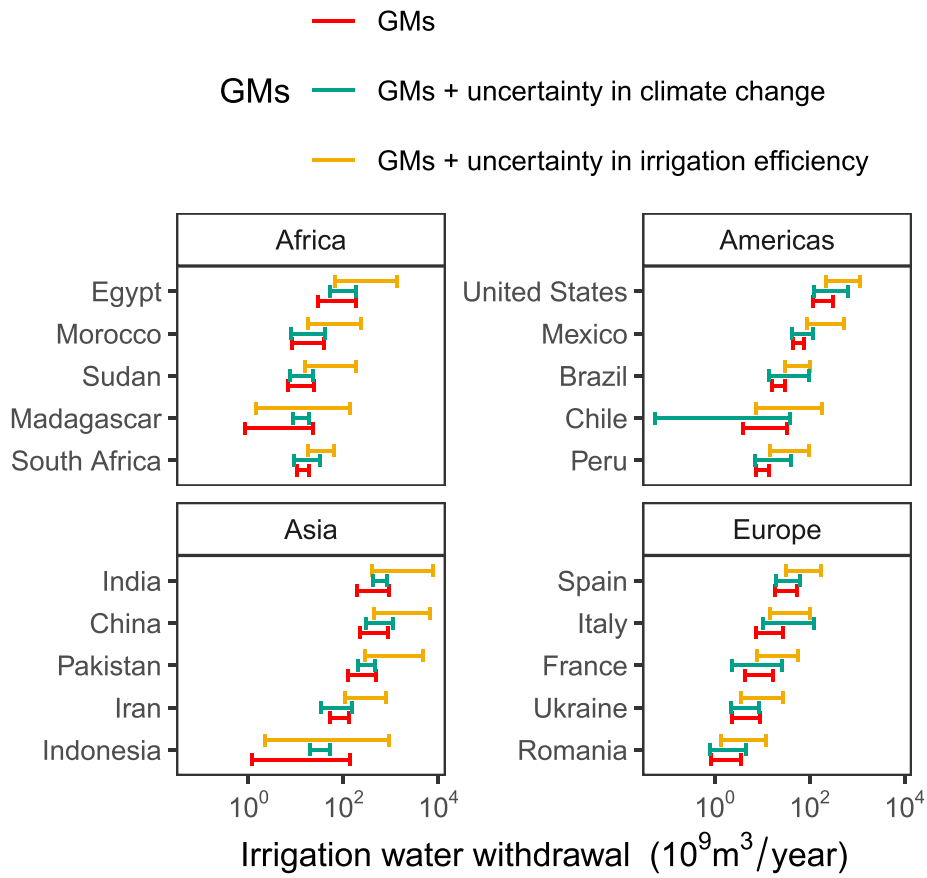

Figure 5. Comparison between the aggregated irrigation water withdrawal estimates produced by WaterGap, LPJmL, H08 and PCR-GLOBWB (GMs) and the aggregated estimates obtained once the uncertainty in climate change and irrigation efficiency is accounted for. The error bars frame the 2.5% and 97.5% quantiles. The 'GMs' and 'GMs + uncertainty in irrigation efficiency' labels show data for 2010 while the 'GMs + uncertainty in climate change' label displays data for 2050. Only the five top countries in irrigation water withdrawals in each continent are plotted. See figures S9 and S10 for a ranking of all countries.

Cyprus, Switzerland, United Arab Emirates) display higher irrigation water withdrawal values under climate change (figure S11).

Finally, we note that the integration of climate change uncertainties produces in some cases ranges that are narrower than the ranges produced by running the GMs alone (e.g. the blue error bar for Indonesia, Pakistan or China is narrower than the red error bar, figure 5). Given that the addition of uncertainties most often expands (and not contracts) the model output uncertainty [65, 66], this feature suggests the presence of errors in the ISI-MIP simulations.

4. Discussion

The irrigation efficiency values used by GMs are problematic. They rely on (and simplify) data produced 40–50 years ago despite all the work on the use, applicability and interpretation of the irrigation efficiency concept developed in the past decades [11, 12, 67]. GMs also sanction a technocratic vision of irrigation that includes sharp categories in the definition of irrigation efficiency values, e.g. large-scale–small-scale, modern–traditional, micro–sprinkler–surface irrigation. These distinct categories are idealized because (1) labels classifying irrigation systems based on physical dimensions are highly contextual, (2) the same irrigated area may combine sprinkler with micro-irrigation or micro with surface irrigation [68, 69], (3) irrigation efficiency values are highly contingent on maintenance and managerial activities besides technological features [70], and (4) remarkably different performances can arise within categories due to differences in design or lack of adjustment to specific features of the irrigated area, such as local topography, rising water scarcity and prevalence of drought.

The idealization of categories is especially apparent in the conceptualization of 'large-scale' irrigated areas and irrigation technologies: firstly, the term 'large-scale' does not necessarily refer to physical dimensions. An irrigation system may also be described as 'large-scale' if managed by an irrigation organization responsible for distributing water to the farmers or by a state, regardless of its dimensions [56]. With this qualitative criteria, very extensive irrigated areas such as the *huerta* of València or Murcia (Spain) (>11 000 ha) would not fit the 'large-scale' category

given their bottom-up, decentralized management [53, 71].

Secondly, the inclusion of surface, sprinkler and micro-irrigation in a sequence of increasingly irrigation-efficient technologies assumes that micro irrigation is always adopted to increase water efficiency because it leads to the largest efficiency gains [26, p 39]. But farmers may also embrace micro-irrigation to reduce workloads, to maintain a landlord status [70], to irrigate steep slopes [72], or simply as a bandwagon effect [73]. Governments can promote micro-irrigation to alleviate poverty or tame more informal, difficult-to-control irrigation [74]. And micro-irrigation may actually increase water consumption at the farm, system and basin levels if it goes alongside the extension of the irrigated area or a switch to more water-intensive crops, a phenomenon known as the rebound effect [75].

Our study reproduces the approach of GMs in computing irrigation efficiency but integrates the main uncertainties characterizing the data they rely upon. We show that these uncertainties impact the estimation of irrigation water withdrawals more than the uncertainties related with climate change: they generally lead to broader ranges and more extreme values at the upper end of the distribution (figures 5, S9 and S10). This relevance contrasts with the much larger attention given to climatic scenarios and their potential effect on irrigation water demands in the scientific literature [48, 49, 76, 77]. Although the existence of irrigation efficiency uncertainties was noted when the concept of irrigation efficiency entered GMs [23, 26], ambiguities received no formal recognition and ended up hidden behind artificially sharp point-estimates. This process fits with what Rayner calls 'displacement' [78, 79], the process by which reality gets substituted by a more manageable surrogate, the model. With the vagueness of irrigation efficiency moved to the background and climate change increasingly permeating the public imagery [80], the study of climatic uncertainties and their effect on irrigation demands has taken center stage in the GMs field. Based on the weight of uncertainties, our results suggest that this order of priorities should be revised.

The use of spuriously precise irrigation efficiency values misguides high level policies relying on model-based irrigation water withdrawal estimates. The extent of this deception may be appreciated with the example of Mexico, whose volume of water withdrawn for irrigation goes from 40–70 10^9 to 80–500 10^9 m^3 after integrating irrigation efficiency uncertainties. For the planning of water storage infrastructures, this means assuming a margin of error equal to the volume of water stored by either 2 or 13 Hoover dams (35 10^9 m^3). At the local level, it equals a measurement error of either 2 million or 16 million smallholder farmers whose access to water might be overlooked (assuming 1 l/s/hectare and 1 ha per smallholder). Note in this case how the uncertainty in irrigation efficiency alone boosts the uncertainty range in water withdrawals by one order of magnitude. In the calculation of irrigation water withdrawals by GMs there are other sources of uncertainty besides irrigation efficiency [32], such as the area under irrigation (hard to precisely define due to unreliable country-based statistical data or sources of error in the remote sensing of irrigated areas [55, 81]), the crop evapotranspiration (there are several equations to compute it and no agreement as to which one works best [82]), or the precipitation dataset (prone to ambiguities due to sparcity in the gauge network, inaccuracy in measurements or errors in data collation and synthesis) [83]. These are likely to expand the uncertainty in the estimation of irrigation water withdrawals even further due to the 'uncertainty cascade' effect [65].

While we value the benefits of more research on irrigation efficiency, we argue that uncertainties in the estimates used by GMs are unlikely to disappear. Firstly, because the collection of field data at the scale required by the simulations is unfeasible. Secondly, because sharp single values may be elusive regardless: a fine-grained study conducted on micro-irrigation plots in Morocco documented a coefficient of variation of 34% for irrigation efficiencies due to different irrigation and maintenance activities [70]. Other ranges may apply elsewhere given the local character of agrarian practices. Thirdly, because by the time the collected data has been introduced in the models, field realities might have changed significantly due to the dynamical nature of agricultural systems [84]. In general, the increase of our knowledge on a specific topic tends to open up unexpected uncertainties not considered in the original problem framing [85]. This is well-known by the climate change community after more than 30 years collecting data on climate sensitivity (the average global warming that would be produced by doubling CO_2 atmospheric concentration from 280 to 560 ppm), leading to ever-larger uncertainties [86].

The ranges proposed in this paper are produced with the irrigation efficiency data underpinning the irrigation efficiency values used by GMs. They are also conditioned by the GMs' factorial approach to irrigation efficiency, known to magnify errors and misrepresent efficiencies [52]. Hence they should not be taken at face value but as evidence of important unattended ambiguities, with critical implications for the production of irrigation water withdrawal estimates and the design of robust policies at the water-agricultural interface. The 'inexact' nature of Hydrology as a science [87] matches poorly with the use of sharp point-estimates: once audited, the rhetorical nature of these numbers (e.g. their use as tools to constrain complexities and confirm pre-existent narratives) is often revealed. In the case of existing ecological or agricultural estimates

this frequently leads to a redefinition, reversal or even a rebuttal of the associated policy implications [88], with the subsequent delay in the design of appropriate responses to social-environmental challenges.

Rather than attempting to drive uncertainties out, GMs might increase their social and policy relevance by thoroughly—and more realistically—exploring their uncertain space, including both quantitative uncertainties and the impact that disciplinary or normative assumptions have in the production of the model output [32, 89]. Opening up the box of the modeling process should be backed up by a disclosure of the conditionalities underpinning the model inferences. This approach minimizes the knowledge asymmetry between modelers and model users (e.g. regulators) and prevents a reductionist framing of the problem, thus circumventing the formation of tunnel visions that would align policies along a single, possibly non-optimal direction.

Data availability statement

The irrigation efficiency data generated in this study is available in Puy [90]. The datasets needed to reproduce our results are available in Puy [90] and in https://github.com/arnaldpuy/irrigation_efficiency. The irrigation water withdrawal estimates produced by GMs can be retrieved in www.isimip.org.

Acknowledgment

A P has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant No. 792178.

Code availability

The R code to replicate our results is available in Puy [90] and in https://github.com/arnaldpuy/irrigation_efficiency.

Author contributions

A P designed the research, retrieved the data and conducted the simulations. A P and A S designed the uncertainty and sensitivity analysis. J M curated the data from the irrigated area maps. A P, B L, J M, S V K and A S interpreted and discussed the results. A P lead the writing of the paper, with major contributions of B L, S V K and A S in the introduction and discussion sections. All authors edited, revised and approved the final version.

ORCID iD

Arnald Puy https://orcid.org/0000-0001-9469-2156

References

[1] Mutiga J K, Mavengano S T, Zhongbo S, Woldai T and Becht R 2010 Water allocation as a planning tool to minimise water use conflicts in the Upper Ewaso Ng'iro North Basin, Kenya *Water Resour. Manage.* **24** 3939–59
[2] United Nations 2019 The sustainable development goals report 2019 *The Sustainable Development Goals Report* (New York: United Nations)
[3] Rockström J *et al* 2009 A safe operating space for humanity *Nature* **461** 472–5
[4] Garrick D *et al* 2019 Rural water for thirsty cities: a systematic review of water reallocation from rural to urban regions *Environ. Res. Lett.* **14** 043003
[5] Karimi P, Bastiaanssen W G and Molden D 2013 Water accounting plus (WA+)—a water accounting procedure for complex river basins based on satellite measurements *Hydrol. Earth Syst. Sci.* **17** 2459–72
[6] McCartney M, Rebelo L M, Xenarios S and Smakhtin V 2013 Agricultural water storage in an era of climate change: assessing need and effectiveness in Africa *IWMI Research Report 152* pp 1–29
[7] World Bank 2008 Agriculture for development *World Development Report 2008* (The World Bank)
[8] Chengot R, Knox J W and Holman I P 2021 Evaluating the feasibility of water sharing as a drought risk management tool for irrigated agriculture *Sustainability* **13** 1–16
[9] Malek K, Adam J C, Stöckle C O and Peters R T 2018 Climate change reduces water availability for agriculture by decreasing non-evaporative irrigation losses *J. Hydrol.* **561** 444–60
[10] Stewart I T, Rogers J and Graham A 2020 Water security under severe drought and climate change: disparate impacts of the recent severe drought on environmental flows and water supplies in Central California *J. Hydrol.* X **7** 100054
[11] Van Halsema G E and Vincent L 2012 Efficiency and productivity terms for water management: a matter of contextual relativism versus general absolutism *Agric. Water Manage.* **108** 9–15
[12] Lankford B *et al* 2020 A scale-based framework to understand the promises, pitfalls and paradoxes of irrigation efficiency to meet major water challenges *Glob. Environ. Change* **65** 102182
[13] Keller A, Keller J and Seckler D 1996 Integrated water resource systems: theory and policy implications *Technical Report* (Colombo: Int. Irrigation Water Management Institute)
[14] Allen R G, Pereira L S, Raes D and Smith M 1998 *Crop evapotranspiration — guidelines for computing crop water requirements. FAO Irrigation and drainage* 56 Food and Agriculture Organization of the United Nations
[15] Doorenbos J and Pruitt W 1977 Guidelines for predicting crop water requirements *Technical Report* (Rome: Food and Agriculture Organization of the United Nations)
[16] Brouwer C, Prins K and Heibloem M 1989 Irrigation water management: irrigation scheduling. training manual no 4 *Technical Report* (Rome: FAO Land and Water Development Division)
[17] Pokhrel Y, Hanasaki N, Koirala S, Cho J, Yeh P J, Kim H, Kanae S and Oki T 2012 Incorporating anthropogenic water regulation modules into a land surface model *J. Hydrometeorol.* **13** 255–69
[18] Hanasaki N, Yoshikawa S, Pokhrel Y and Kanae S 2018 A global hydrological simulation to specify the sources of water used by humans *Hydrol. Earth Syst. Sci.* **22** 789–817
[19] Müller Schmied H *et al* 2021 The global water resources and use model WaterGAP v2.2d: model description and evaluation *Geosci. Model Dev.* **14** 1037–79
[20] Wisser D, Frolking S, Douglas E M, Fekete B M, Vörösmarty C J and Schumann A H 2008 Global irrigation water demand: variability and uncertainties arising from agricultural and climate data sets *Geophys. Res. Lett.* **35** 1–5

[21] Rost S, Gerten D, Bondeau A, Lucht W, Rohwer J and Schaphoff S 2008 Agricultural green and blue water consumption and its influence on the global water system *Water Resour. Res.* **44** 1–17
[22] Wada Y, Van Beek L P and Bierkens M F 2011 Modelling global water stress of the recent past: on the relative importance of trends in water demand and climate variability *Hydrol. Earth Syst. Sci.* **15** 3785–808
[23] Döll P and Siebert S 2002 Global modeling of irrigation water requirements *Water Resour. Res.* **38** 8–1–8–10
[24] Wada Y *et al* 2016 Modeling global water use for the 21st century: The Water Futures and Solutions (WFaS) initiative and its approaches *Geosci. Model Dev.* **9** 175–222
[25] Jägermeyr J, Gerten D, Heinke J, Schaphoff S, Kummu M and Lucht W 2015 Water savings potentials of irrigation systems: global simulation of processes and linkages *Hydrol. Earth Syst. Sci.* **19** 3073–91
[26] Rohwer J, Gerten D and Lucht W 2007 Development of functional irrigation types for improved global crop modelling *PIK Rep.* **1–61** 9
[27] Veldkamp T I *et al* 2018 Human impact parameterizations in global hydrological models improve estimates of monthly discharges and hydrological extremes: a multi-model validation study *Environ. Res. Lett.* **13** 055008
[28] Di Baldassarre G *et al* 2019 Sociohydrology: scientific challenges in addressing the sustainable development goals *Water Resour. Res.* **55** 6327–55
[29] Saltelli A, Guimaraes Pereira A, van der Sluijs J P and Funtowicz S O 2013 What do I make of your Latinorum? Sensitivity auditing of mathematical modelling *Int. J. Innov. Policy* **9** 213–34
[30] Saltelli A, Ratto M, Andres T, Campolongo F, Cariboni J, Gatelli D, Saisana M and Tarantola S 2008 *Global Sensitivity Analysis. The Primer* (Chichester: Wiley)
[31] Puy A, Borgonovo E, Lo Piano S, Levin S A and Saltelli A 2021 Irrigated areas drive irrigation water withdrawals *Nat. Commun.* **12** 4525
[32] Puy A, Sheikholeslami R, Gupta H V, Hall J W, Lankford B, Lo Piano S, Meier J, Pappenberger F, Porporato A, Vico G and Saltelli A 2021 Supplementary materials for The delusive accuracy of global irrigation water withdrawal estimates (v1.0.4) *Zenodo* (https://doi.org/10.5281/zenodo.5528844)
[33] Shi H, Chen J, Liu S and Sivakumar B 2019 The role of large dams in promoting economic development under the pressure of population growth *Sustainability* **11** 1–14
[34] Shivakoti B R, Villholth K G, Pavelic P and Ross A 2019 Strategic use of groundwater-based solutions for drought risk reduction and climate resilience in Asia and beyond *Technical Report* (United Nations Office for Disaster Risk Reduction)
[35] Fader M, Shi S, Von Bloh W, Bondeau A and Cramer W 2016 Mediterranean irrigation under climate change: more efficient irrigation needed to compensate for increases in irrigation water requirements *Hydrol. Earth Syst. Sci.* **20** 953–73
[36] Sutanudjaja E H *et al* 2018 PCR-GLOBWB 2.0: a 5 arc-minute global hydrological and water resources model *Geosci. Model Dev.* **11** 2429–53
[37] Bos M and Nugteren J 1990 On irrigation efficiencies *Technical Report* (Wageningen: Int. Institute for Land Recamation and Improvement / ILRI)
[38] FAO 1997 Irrigation potential in Africa. A basin approach. FAO land and water bulletin 4 *Technical Report* (Rome: Food and Agriculture Organization of the United Nations)
[39] Guera L C, Bhuiyan S I, Tuong T P and Barker R 1998 Producing more rice with less water from irrigated Systems *Technical Report* (Manila: Int. Rice Research Institute)
[40] Solley W B, Pierce R R and Perlman H 1998 Estimated use of water in the United States in 1995 *Technical Report* US Geological Survey Circular 1200 50
[41] Fairweather H, Austin N and Hope M 2004 Water use efficiency. an information package. Irrigation Insights Number 5 *Technical Report 2* Canberra Land & Water Australia. National Program for Sustainable Irrigation Canberra
[42] Rogers D, Lamm F, Alam M, Trooien T, Barnes G C P and Mankin K 1997 *Efficiencies and water losses of irrigation systems. Irrigation Management Series* Kansas State University, USA
[43] Commission E 2021 Better regulation toolbox (available at: https://ec.europa.eu/info/law/law-making-process/planning-and-proposing-law/better-regulation-why-and-how/better-regulation-guidelines-and-toolbox_en)
[44] Hanasaki N, Kanae S, Oki T, Masuda K, Motoya K, Shirakawa N, Shen Y and Tanaka K 2008 An integrated model for the assessment of global water resources—Part 2: applications and assessments *Hydrol. Earth Syst. Sci.* **12** 1027–37
[45] Wada Y, Wisser D and Bierkens M F P 2014 Global modeling of withdrawal, allocation and consumptive use of surface water and groundwater resources *Earth Syst. Dyn.* **5** 15–40
[46] Haddeland I *et al* 2014 Global water resources affected by human interventions and climate change *Proc. Natl Acad. Sci. USA* **111** 3251–6
[47] ISI-MIP 2021 Model information and data caveats from ISIMIP Fast Track (available at: www.isimip.org/outputdata/caveats-fast-track/)
[48] Döll P 2002 Impact of climate change and variability on irrigation requirements: a global perspective *Clim. Change* **54** 269–93
[49] Alcamo J, Flörke M and Märker M 2007 Future long-term changes in global water resources driven by socio-economic and climatic changes *Hydrol. Sci. J.* **52** 247–75
[50] Sanaee-Jahromi S, Feyen J, Wyseure G and Javan M 2001 Approach to the evaluation of undependable delivery of water in irrigation schemes *Irrig. Drain. Syst.* **15** 197–213
[51] Siebert S, Döll P, Hoogeveen J, Faures J M, Frenken K and Feick S 2005 Development and validation of the global map of irrigation areas *Hydrol. Earth Syst. Sci.* **9** 535–47
[52] Lankford B 2012 Fictions, fractions, factorials and fractures; on the framing of irrigation efficiency *Agric. Water Manage.* **108** 27–38
[53] Ostrom E 1990 *Governing the Commons: The Evolution of Institutions for Collective Action* (Cambridge: Cambridge University Press)
[54] Meier J, Zabel F and Mauser W 2018 A global approach to estimate irrigated areas. A comparison between different data and statistics *Hydrol. Earth Syst. Sci.* **22** 1119–33
[55] Thenkabail P S *et al* 2009 Global irrigated area map (GIAM), derived from remote sensing, for the end of the last millennium *Int. J. Remote Sens.* **30** 3679–733
[56] Lankford B, Makin I, Matthews N, Mccornick P and Noble A 2016 A compact to revitalise large-scale irrigation systems using a leadership-partnership-ownership theory of change *Water Altern.* **9** 1–32
[57] Siebert S, Kummu M, Porkka M, Döll P, Ramankutty N and Scanlon B R 2015 A global data set of the extent of irrigated land from 1900 to 2005 *Hydrol. Earth Syst. Sci.* **19** 1521–45
[58] Salmon J, Friedl M A, Frolking S, Wisser D and Douglas E M 2015 Global rain-fed, irrigated and paddy croplands: a new high resolution map derived from remote sensing, crop inventories and climate data *Int. J. Appl. Earth Obs. Geoinf.* **38** 321–34
[59] Puy A, Lo Piano S, Saltelli A and Levin S 2021 A sensobol: an R package to compute variance-based sensitivity indices (arXiv: 2101.10103 [stat.CO])
[60] Sobol' I M 1967 On the distribution of points in a cube and the approximate evaluation of integrals *USSR Computat. Math. Math. Phys.* **7** 86–112
[61] Sobol' I M 1976 Uniformly distributed sequences with an additional uniform property *USSR Computat. Math. Math. Phys.* **16** 236–42
[62] Puy A, Becker W, Lo Piano S and Saltelli A 2022 A comprehensive comparison of total-order estimators for global sensitivity analysis *Int. J. Uncertain. Quantification* **12** 1–18

[63] Clemmens A J and Molden D J 2007 Water uses and productivity of irrigation systems *Irrig. Sci.* **25** 247–61
[64] Lam W F 1996 Improving the performance of small-scale irrigation systems: the effects of technological investments and governance structure on irrigation performance in Nepal *World Dev.* **24** 1301–15
[65] Smith K A, Wilby R L, Broderick C, Prudhomme C, Matthews T, Harrigan S and Murphy C 2018 Navigating cascades of uncertainty—as easy as ABC? not quite… *J. Extreme Events* **05** 1850007
[66] O'Neill R V 1971 Error analysis of ecological models *Proc. of the Third Symp. on Radioecology, (Oak Ridge, Tennessee, 10–12 May 1971)* ed D J Nelson
[67] Seckler D 1996 The new era of water resources management *Research Report 1* (Colombo: Int. Irrigation Management Institute)
[68] Puy A, García Avilés J M, Balbo A L, Keller M, Riedesel S, Blum D and Bubenzer O 2017 Drip irrigation uptake in traditional irrigated fields: the edaphological impact *J. Environ. Manage.* **202** 550–61
[69] Van der Kooij S 2016 Performing drip irrigation by the farmer managed Seguia Khrichfa irrigation system, Morocco *Doctoral dissertation*, Wageningen University and Research
[70] Benouniche M, Kuper M, Hammani A and Boesveld H 2014 Making the user visible: analysing irrigation practices and farmers' logic to explain actual drip irrigation performance *Irrig. Sci.* **32** 405–20
[71] Martínez-Fernández J 2000 Selma M A E and Calvo-Sendín J F Environmental and socio-economical interactions in traditional irrigated lands: a dynamic system model *Human Ecol.* **28** 279–99
[72] Van der Kooij S, Zwarteveen M, Boesveld H and Kuper M 2013 The efficiency of drip irrigation unpacked *Agric. Water Manage.* **123** 103–10
[73] Verma S, Tsephal S and Jose T 2004 Pepsee systems: grassroots innovation under groundwater stress *Water Policy* **6** 303–18
[74] Venot J P *et al* 2014 Beyond the promises of technology: a review of the discourses and actors who make drip irrigation *Irrig. Drain.* **63** 186–94
[75] Ghoreishi M, Sheikholeslami R, Elshorbagy A, Razavi S and Belcher K 2021 Peering into agricultural rebound phenomenon using a global sensitivity analysis approach *J. Hydrol.* **602** 126739
[76] Wada Y *et al* 2013 Multimodel projections and uncertainties of irrigation water demand under climate change *Geophys. Res. Lett.* **40** 4626–32
[77] Woznicki S A, Nejadhashemi A P and Parsinejad M 2015 Climate change and irrigation demand: uncertainty and adaptation *J. Hydrol.: Reg. Stud.* **3** 247–64
[78] Ravetz J R 1986 Usable knowledge, usable ignorance: incomplete science with policy implications *Sustainable Development of the Biosphere* ed W Clar and R Munn (New York: IIASA/Cambridge University Press) pp 415–32
[79] Rayner S 2012 Uncomfortable knowledge: the social construction of ignorance in science and environmental policy discourses *Economy and Society* **41** 107–25
[80] Saltelli A and Boulanger P 2020 A climate of dialogue *Dimensions of Intra-and Intergenerational Justice in the Debates About Sustainability* ed S Serafimova (Sofia: Avangard Prima) pp 69–99
[81] Ajaz A, Karimi P, Cai X, Fraiture C D and Akhter M S 2019 Statistical data collection methodologies of irrigated areas and their limitations: a review *Irrig. Drain.* **68** 702–13
[82] Fisher J B, Whittaker R J and Malhi Y 2011 ET come home: potential evapotranspiration in geographical ecology *Glob. Ecol. Biogeogr.* **20** 1–18
[83] Meehl G A *et al* 2007 Global climate projections Climate Change *2007 The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the IPCC* ed S Solomon, D Qin, M Manning, M Marquis, K Averyt, M M B Tignor, H LeRoy Miller Jr and Z Chen (Cambridge: Cambridge University Press) pp 746–845
[84] Massuel S, Riaux J, Molle F, Kuper M, Ogilvie A, Collard A L, Leduc C and Barreteau O 2018 Inspiring a broader socio-hydrological negotiation approach with interdisciplinary field-based experience *Water Resour. Res.* **54** 2510–22
[85] Giampietro M 2015 Foreword *Science, Philosophy and Sustainability. The End of the Cartesian Dream* ed Â Guimarães Pereira and S Funtowicz (New York: Routledge) pp 13–14
[86] Van der Sluijs J P 2016 Numbers running wild *The Rightful Place of Science: Science on the Verge* ed A Benessia, S Funtowickz, M Giampietro, A Guimaraes Pereira, J Ravetz, A Saltelli, J P van der Sluijs and R Strand (Tempe: Consortium for Science, Policy & Outcomes, Arizona State University) pp 151–87
[87] Beven K 2019 Towards a methodology for testing models as hypotheses in the inexact sciences *Proc. R. Soc.* A **475** 20180862
[88] Pilkey O H and Pilkey-Jarvis L 2009 *Useless Arithmetic: Why Environmental Scientists Can't Predict the Future* (New York: Columbia University Press)
[89] Saltelli A *et al* 2020 Five ways to ensure that models serve society: a manifesto *Nature* **582** 482–4
[90] Puy A 2021 R code of the paper Large variations in global irrigation withdrawals caused by uncertain irrigation efficiencies *Zenodo* (https://doi.org/10.5281/zenodo.5551973)