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Global irrigation water demand: Variability and uncertainties arising from agricultural and climate data sets

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Global irrigation water demand: Variability and uncertainties arising from agricultural and climate data sets

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[1] Agricultural water use accounts for around 70% of the total water that is withdrawn from surface water and groundwater. We use a new, gridded, global-scale water balance model to estimate interannual variability in global irrigation water demand arising from climate data sets and uncertainties arising from agricultural and climate data sets. We used contemporary maps of irrigation and crop distribution, and so do not account for variability or trends in irrigation area or cropping. We used two different global maps of irrigation and two different reconstructions of daily weather 1963–2002. Simulated global irrigation water demand varied by ~30%, depending on irrigation map or weather data. The combined effect of irrigation map and weather data generated a global irrigation water use range of 2200 to 3800 km^3 a^{-1}. Weather driven variability in global irrigation was generally less than ±300 km^3 a^{-1}, globally (<~10%), but could be as large as ±70% at the national scale. **Citation:** Wisser, D., S. Frolking, E. M. Douglas, B. M. Fekete, C. J. Vörösmarty, and A. H. Schumann (2008), Global irrigation water demand: Variability and uncertainties arising from agricultural and climate data sets, *Geophys. Res. Lett.*, *35*, L24408, doi:10.1029/2008GL035296.

1. Introduction

[2] Water withdrawals for agriculture account for ~72% of the total water that is withdrawn from surface water and groundwater globally, and ~90% in developing countries [*Cai and Rosegrant*, 2002]. While small relative to the overall water cycle (~8% of global discharge to the oceans), the regional impacts on the hydrological cycle can be dramatic, transforming large, mainstem rivers into 'losing streams' with substantial reductions in flow. Excess drainage from irrigated areas can sustain unnaturally high winter streamflow [*Kendy and Bredehoeft*, 2006].

[3] Despite its significance for food security and the global water cycle, the extent and distribution of irrigated areas on a global scale remain highly uncertain [*Vörösmarty*, 2002]. Estimates of irrigation water withdrawals are not only constrained directly by uncertainty in irrigated area, but also indirectly by uncertainties in spatial distribution of factors that influence the demand for irrigation water: (1) soil hydraulic parameters, (2) crop areas, (3) weather, and (4) growing season timing and how it correlates with water availability.

[4] In addition to substantial uncertainty, there is interannual variability in actual irrigation water demand, driven by variability in precipitation and evaporative demand, as well as variability in cropping patterns. As research begins to evaluate the implications of climate change for irrigated agriculture [e.g., *Jones*, 2000; *Droogers and Aerts*, 2005], it is important to quantify interannual variability, as it is the extreme years that exert the most impact on agricultural production [e.g., *Thomas*, 2008]. We used a water balance model to estimate uncertainties in global and regional irrigation water withdrawal. We also assessed the global and regional variability in irrigation water demand due to interannual variability in precipitation and temperature, and the spatial and temporal differences that exist in global precipitation datasets.

2. Model, Data, and Methods

[5] WBM$_{plus}$ is a modified version of WBM [*Vörösmarty et al.*, 1998] that simulates irrigation water use globally at 30 min spatial resolution. For each grid cell, we calculated daily irrigation water demand (section 2.1) by combining data on irrigated area (2.2.1), growing season (2.2.2), cropping patterns (2.2.3), soil properties (2.2.4), and daily weather (2.3), and aggregated this to annual irrigation water demand at national to global scales.

2.1. Irrigation Water Demand Model

[6] Irrigation water requirement per unit crop area was estimated with the crop coefficient method [*Allen et al.*, 1998], which is widely used to design and operate irrigation schemes and has previously been applied in macroscale hydrological [e.g., *Döll and Siebert*, 2002; *Haddeland et al.*, 2006] and land surface [*de Rosnay et al.*, 2003] models. Daily crop evapotranspiration, E$_c$ (*mm* d^{-1}), was estimated as:

$$E_c = k_c ET_0 \qquad (1)$$

where k_c is a dimensionless crop coefficient that represents time-varying crop physiological parameters, and ET_0 (*mm* d^{-1}) is the reference evapotranspiration, computed in our analysis using the temperature-dependent [*Hamon*, 1963] method. WBM$_{plus}$ then calculates a daily soil moisture balance of precipitation and E_c. Irrigation water, I_{net} (*mm* d^{-1}), is applied to refill the soil to field capacity

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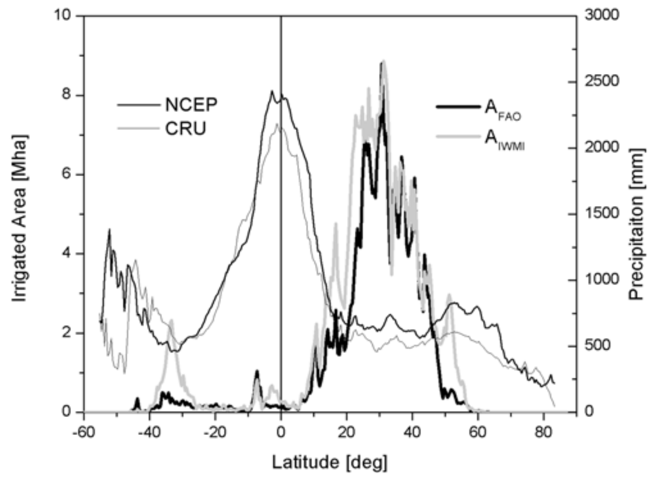

Figure 1. Latitude profiles (0.5° bins) of irrigated area, using the A_{FAO} and A_{IWMI} maps, and mean annual precipitation over all land (1963–2002) for CRU and NCEP precipitation.

whenever the soil moisture level drops below a critical, crop-dependent threshold [*Allen et al.*, 1998]. Water in excess of the soil water capacity is considered to percolate and recharge groundwater.

[7] We assumed that irrigation water is applied to paddy rice to maintain a 50 mm flooding depth until 10 days before harvest, and that flooded water percolates down out of the root zone at a constant rate that depends on the grid cell soil drainage class, estimated spatially from the FAO soil map of the world [*Food and Agriculture Organization of the United Nations (FAO)*, 2002] as: 8 *mm* d^{-1} for 'extremely well-drained soils', 5 *mm* d^{-1} for 'well-, moderately-, and imperfectly-drained' soils, and 2 *mm* d^{-1} for 'poorly and very poorly drained soils'. This is within the range of low and high percolation losses for paddy rice of 200 and 700 *mm* per crop season reported by *FAO* [2004].

[8] Water withdrawals must be greater than crop demand because of conveyance losses and evaporation. The total irrigation water requirement, I_{gross}, accounts for irrigation inefficiency losses:

$$I_{gross} = \frac{I_{net}}{E_{eff}} \tag{2}$$

where E_{eff} is the project or irrigation efficiency (values from *Döll and Siebert* [2002]; range = 0.35 – 0.7). In this analysis, we assume that there are no water supply limitations, so irrigation can always meet all demand.

2.2. Agricultural Data Sets

2.2.1. Irrigated Area Maps

[9] There are currently two global, spatial data sets of irrigated areas around the year 2000: the FAO/University of Frankfurt Global Map of Irrigated Areas GMIA (hereafter A_{FAO}) [*Siebert et al.*, 2005, 2007], and the Global Irrigated Area Map (GIAM), recently prepared by the International Water Management Institute (hereafter A_{IWMI}) [*Thenkabail et al.*, 2006]. Both maps have been aggregated to 30 min resolution.

[10] A_{FAO} reports 'areas equipped for irrigation' at 5-min resolution. The total area in Version 4.0.1 is 279 Mha. We determined the irrigation pattern in each grid cell using irrigation intensity values from *FAO* [2008]. For values >1, we assumed that all of the mapped irrigated area is irrigated in the wet season (climatologically determined from the CRU weather data time series), and that the remaining fraction is also irrigated in the dry season (e.g., an irrigation intensity of 1.2 implies 20% has two irrigated cropping seasons per year, and 80% has one). We assumed an irrigation intensity of 1.0 if there was no reported value. If the irrigation intensity is less than one, we assumed that only that fraction of the reported equipped area was irrigated. This resulted in a global harvested irrigated area of 320 Mha. A_{FAO} data may underestimate small-scale informal irrigation, but it may also overestimate actual irrigated area by including large but unused or damaged irrigation infrastructure [*Siebert and Döll*, 2007].

[11] A_{IWMI} mapped 'actual irrigated areas' at 1-km globally, based on optical remote sensing and other data. Version 2 reports areas separately for 28 crop-rotation and water use classes and for each growing season. The total harvested irrigated area, the sum of areas for all growing seasons, is 446 Mha, ~40% more than A_{FAO}. The two data sets agree in broad spatial patterns (Figure 1), but have significant differences in individual countries. Nearly two-thirds of the total difference occurs in India ($A_{IWMI} \sim 1.36 \times A_{FAO}$) and China ($A_{IWMI} \sim 1.54 \times A_{FAO}$). The cropping intensity for A_{IWMI} data is implicitly given through seasonal reporting. Crop distributions (described below) were assumed to be the same in each season for both irrigation area maps.

2.2.2. Growing Season Pattern

[12] To determine the onset of the growing season in the temperate zone, we used a simple temperature threshold and assumed that the growing season starts on the first day of the first month with mean air temperature >5°C. In areas where the growing season is not limited by temperature, we determined the wet (or wettest) season based on the monthly values of the precipitation data and assumed that the growing season starts on the first day of the month before the month with the maximum rainfall in a given year. If multiple cropping is possible, the second season is assumed to start 150 days after the start of the first season.

2.2.3. Cropping Pattern

[13] *Monfreda et al.* [2008] compiled a global, 5-min resolution data set of year 2000 harvested areas for 175 crops. Variability in k_c (equation (1)) among similar crops is small compared to uncertainties in crop distribution and extent, so we aggregated the 175 crops into four crop groups: seasonal, (paddy) rice, vegetables, and perennials, and used average k_c values for those crop groups, computed from *Allen et al.* [1998]. We aggregated this data to 30-min resolution and distributed crop areas proportionally over the irrigated areas. If grid cells were designated as irrigated but had no cropland area (~10% of A_{FAO} grid cells, ~6% for A_{IWMI}) we assumed that there was an irrigated seasonal crop (the lowest water requirement).

2.3. Weather Drivers

[14] The WBM_{plus} model as implemented (with Hamon ET_0 function) requires daily air temperature and precipitation. We used two global climate data sets to explore the interannual climate-driven variability and uncertainty of modeled irrigation water demand; the observation-

Table 1. Global and Some National Values of Interannual Climate-Driven Variability in Simulated, Annual Irrigation Water Withdrawals[a]

Region Weather Data Irrigation Area Map	Mean	20–80%	Min–Max	*Döll and Siebert* [2002][b]	*FAO* [2008][c]
Global				2452	2659
CRU/A_{FAO}	3100	3100–3200	3000–3400		
CRU/A_{IWMI}	3800	3800–3900	3700–4100		
NCEP/A_{FAO}	2200	2100–2200	2000–2400		
NCEP/A_{IWMI}	2700	2600–2800	2500–3000		
India				655	558
CRU/A_{FAO}	850	820–870	800–910		
CRU/A_{IWMI}	1700	1700–1700	1600–1800		
NCEP/A_{FAO}	510	480–550	390–590		
NCEP/A_{IWMI}	1300	1200–1300	1100–1400		
China				352	427
CRU/A_{FAO}	610	580–630	540–690		
CRU/A_{IWMI}	760	730–780	690–850		
NCEP/A_{FAO}	350	300–400	220–480		
NCEP/A_{IWMI}	420	360–470	270–600		
Egypt				60	59
CRU/A_{FAO}	38	37–39	36–41		
CRU/A_{IWMI}	19	18–19	18–20		
NCEP/A_{FAO}	35	34–38	31–36		
NCEP/A_{IWMI}	17	16–17	15–18		
USA				186	198
CRU/A_{FAO}	140	130–150	130–140		
CRU/A_{IWMI}	120	120–130	110–140		
NCEP/A_{FAO}	120	100–130	87–150		
NCEP/A_{IWMI}	96	82–110	66–130		

[a]Values ($km^3\ a^{-1}$) reported to 2 significant figures.
[b]Calculations are based on a previous version of GMIA and CRU data.
[c]Values include water withdrawal for livestock for some countries.

based, gridded, monthly CRU TS 2.1 product [*Mitchell and Jones*, 2005], hereafter CRU, and the daily NCEP/NCAR reanalysis product [*Kalnay et al.*, 1996], hereafter NCEP. We stochastically downscaled monthly CRU precipitation to generate daily precipitation [*Geng et al.*, 1986]. NCEP annual precipitation is generally higher than CRU (Figure 1).

2.4. Model Simulations

[15] Using both CRU and NCEP weather data, we computed the annual irrigation water withdrawal for 1963 to 2002 for both the A_{FAO} and A_{IWMI} irrigation area maps, assuming constant irrigated area. Irrigation area expanded significantly during this period [*Postel*, 1993], so our analysis is not historical, but an estimate of interannual climate-driven variability in contemporary irrigation water use, and we report only means and variabilities. To test the sensitivity of our estimates to uncertainties in input data, we compared results for the two climate data sets and the two irrigated area maps. We also ran the model, using the A_{FAO}/CRU data, with ±50% soil percolation rates for paddy rice, a 50% increase in soil water holding capacity, all crops as upland annuals, and a constant growing onset determined from the climatological record of the climate drivers.

3. Results and Discussion

3.1. Annual Irrigation Water Withdrawal

[16] Using the A_{FAO} map, we estimate a 40-yr mean irrigation water withdrawal of 3100 $km^3\ a^{-1}$ globally with CRU climate data, and 2200 $km^3\ a^{-1}$ with NCEP data; these fall in the range of previously reported values using A_{FAO} data [*World Resources Institute*, 1998; *Hanasaki et al.*, 2007; *Döll and Siebert*, 2002; *Siebert and Döll*, 2007; *Vörösmarty et al.*, 2005]. When the A_{IWMI} map is used, the computed withdrawal based on CRU and NCEP data are 3800 $km^3\ a^{-1}$ and 2700 $km^3\ a^{-1}$, respectively, a ~30% increase over the A_{FAO} results. For a given irrigation base map, the computed global withdrawal is ~30% lower when forced with NCEP data than CRU data (Table 1), as NCEP precipitation is higher over most irrigated areas (Figure 1). These estimates assume that crops are disease-free and evapotranspiring at the theoretical maximum rate, so they represent an upper bound of expected values.

[17] Simulated mean annual irrigation water demand, aggregated by country, correlates with national statistics reported by *FAO* [2008], though for many countries our simulation results are biased low (Figure 2). This bias is largest for the NCEP/A_{IWMI} simulations. However, national reported values of the actual irrigation water withdrawal are reasonably accurate only for a few regions [*Döll and Siebert*, 2002] and some are incomplete or grossly outdated [*Gleick*, 2003]. It is also likely that many reported national totals are based on water use modeling (methodologically similar to our analysis) and not on actual water-use statistics.

3.2. Inter-annual Variability

[18] From a water resources point of view, it is important to look beyond mean annual water requirements to variations in requirements for dry and wet years. Globally, the range in interannual variability was ~10% of the mean for CRU data and ~20% of the mean for NCEP data (Table 1), smaller than the differences in means arising from base maps of irrigated area or climate drivers. For individual countries, the range in climate-driven variability in irrigation water demand can range from ~10% (e.g., Egypt using CRU/A_{IWMI}) to >70% (e.g. China using NCEP/A_{IWMI} data) (Table 1). *Thomas* [2008] also noted the importance of interannual variability in anticipating future irrigation water requirements in China. Our computed relative interannual variability is lowest in arid areas that are entirely dependent on irrigation for crop productivity, affirming the results *Haddeland et al.* [2006] found for the Mekong and Colorado River basins.

3.3. Sensitivity to Other Variations in Input Data

[19] Model results were very sensitive to factors related to paddy rice, and much less sensitive to other factors. Changing the percolation rate for paddy rice by ±50% caused a ±10% change in global irrigation water use, implying that, in these simulations, ~20% of global irrigation water percolates from flooded fields. These calculations are based on continuous flooding; paddy water management in some regions is changing to intermittent drainage [e.g., *Li et al.*, 2002], reducing total irrigation water requirements. Neglecting cropping information by assuming that only one, non-rice crop is grown on all irrigated land reduced irrigation demand by 50%, again highlighting the importance of paddy rice. Sensitivities to changes in soil water holding capacity and the timing of the growing season were very low (<1%). Further sources of uncertainties not investigated here include variations in the irrigation inten-

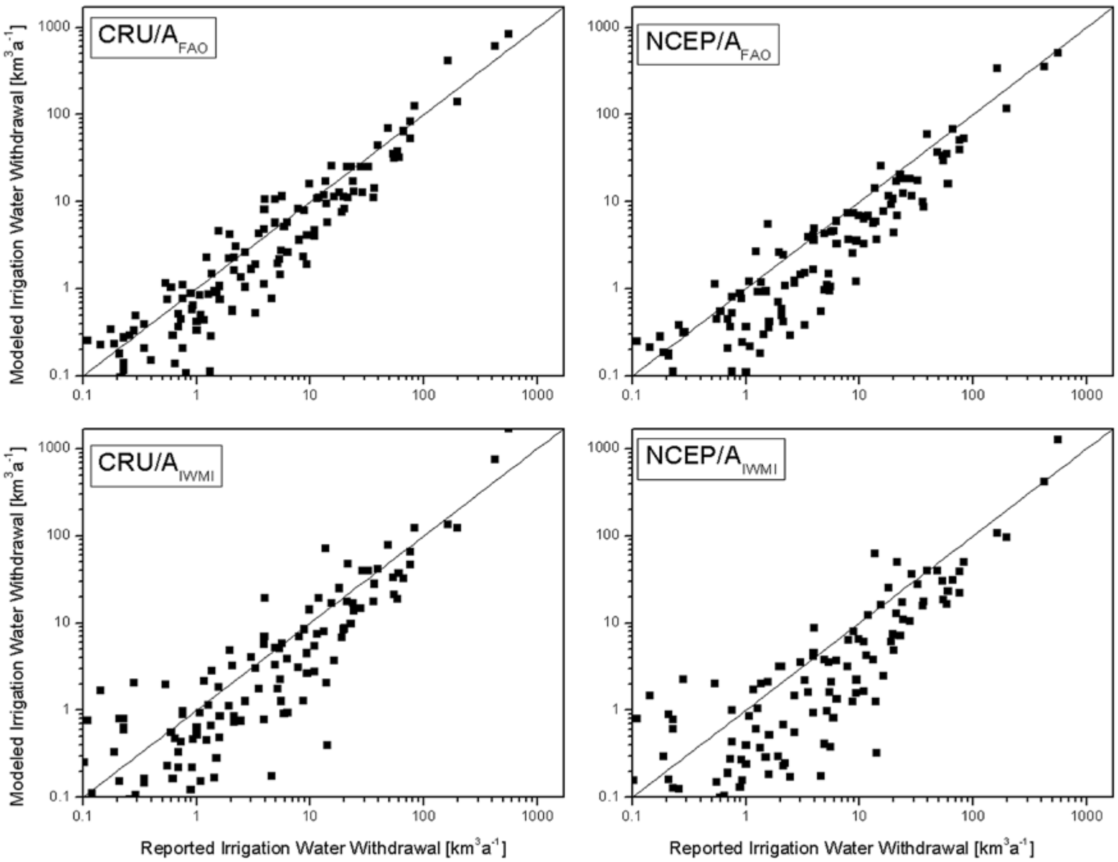

Figure 2. Modeled irrigation water withdrawal per country for different irrigated area and weather data configurations compared with reported agricultural water withdrawal from *FAO* [2008] for 159 countries. 1:1 lines added to each plot. Agricultural water withdrawal includes withdrawals for livestock in some countries.

sity, the ET_0 function, which could change the estimated demand by up to 40% [*Weiss and Menzel*, 2008], and variations in k_c, which might have a 15% sensitivity [*Satti et al.*, 2004].

4. Summary and Conclusions

[20] National and global estimates of irrigation water withdrawal are very sensitive to several key factors that are not well-constrained in existing global datasets: total irrigated area, paddy rice area, percolation rates in paddy soils, overall irrigation efficiencies, and weather (particularly precipitation), which are quantified here for the first time. Of these, paddy rice area is probably the least uncertain; new crop maps continue to improve [*Monfreda et al.*, 2008], but reliable estimates of multiple cropping are difficult to construct [*Frolking et al.*, 2006]. Water percolation rates from paddy soils are not well-constrained, as global soil texture maps are spatially too coarse to reliably assign values to the portion of a model grid cell that is paddy rice. Total irrigated area remains problematic, as national maps are of varying quality [*Döll and Siebert*, 2002], irrigation infrastructure goes out of and comes into service from year to year for economic and technical reasons, and global mapping by remote sensing has several obstacles (clouds, small field size, paddy irrigation in humid environments), though new methodologies are being developed [e.g., *Ozdogan and Gutman*, 2008]. The large differences in irrigation estimates (30%) due to different weather drivers highlight the need for continuing improvements in historical global weather reconstruction and reanalysis products that should remain a global change research priority [*Fekete et al.*, 2004].

[21] The irrigation efficiency values are based on a limited amount of actual field data; the values used represent broad patterns [*Döll and Siebert*, 2002] and likely are close to general mean values, but sub-national spatial and temporal variability is not well-known and constrained by a lack of consistent and accurate quantitative data [*Lankford*, 2006]. Interannual climate-driven variability in global irrigation water use is generally less than 10% of total use, much smaller than the uncertainties due to different climate and irrigation data sets, though it is higher at the regional or national scale and in extremely wet or dry years. This represents an actual interannual variability in irrigation water requirements, and thus should not be compared directly with the larger uncertainties in global demand due to uncertainties in the irrigation area maps or climate fields. It could be compared with actual interannual variability in other factors – paddy rice area, irrigated area of other crops, fraction of irrigation infrastructure that is broken – but these are generally not well-documented. It is also important to bear in mind that years with high weather-driven irrigation water demand are years with low precipitation, and thus are also generally likely to be years with reduced water supply,

increasing the challenge for regional water resource managers, who must supply more water in a dry year.

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