Nonsustainable groundwater sustaining irrigation: A global assessment

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[1] Water used by irrigated crops is obtained from three sources: local precipitation contributing to soil moisture available for root water uptake (i.e., green water), irrigation water taken from rivers, lakes, reservoirs, wetlands, and renewable groundwater (i.e., blue water), and irrigation water abstracted from nonrenewable groundwater and nonlocal water resources. Here we quantify globally the amount of nonrenewable or nonsustainable groundwater abstraction to sustain current irrigation practice. We use the global hydrological model PCR-GLOBWB to simulate gross crop water demand for irrigated crops and available blue and green water to meet this demand. We downscale country statistics of groundwater abstraction by considering the part of net total water demand that cannot be met by surface freshwater. We subsequently confront these with simulated groundwater recharge, including return flow from irrigation to estimate nonrenewable groundwater abstraction. Results show that nonrenewable groundwater abstraction contributes approximately 20% to the global gross irrigation water demand for the year 2000. The contribution of nonrenewable groundwater abstraction to irrigation is largest in India (68 km^3 yr^{-1}) followed by Pakistan (35 km^3 yr^{-1}), the United States (30 km^3 yr^{-1}), Iran (20 km^3 yr^{-1}), China (20 km^3 yr^{-1}), Mexico (10 km^3 yr^{-1}), and Saudi Arabia (10 km^3 yr^{-1}). Results also show that globally, this contribution more than tripled from 75 to 234 km^3 yr^{-1} over the period 1960–2000.

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1. Introduction

[2] Irrigated crops play a vital role in the securing global food production. It is estimated that 17% of agricultural lands are irrigated, yet they account for 40% of the global food production, sustaining the livelihood of billions of people [*Abdullah*, 2006]. At the same time, water used by irrigated crops (i.e., crop water demand) and irrigation water demand (including evaporative and percolation losses during transport and application) are responsible for about 70% of the global water withdrawal [*Shiklomanov*, 2000] and account for about 90% of the global water consumption, i.e., water withdrawal minus return flow [*Döll et al.*, 2009; *Siebert et al.*, 2010].

[3] Water demand for irrigated crops can be met by three different sources: (1) green water, being water from local precipitation that is temporarily stored in the soil, (2) blue water, being surface freshwater available in rivers, lakes, reservoirs and wetlands, and renewable groundwater, and (3) nonrenewable groundwater and nonlocal water resources [*Vörösmarty et al.*, 2005]. The latter comprises water transported by cross-basin diversions, water from desalinization plants, and nonrenewable groundwater abstracted from aquifers. We explicitly use the term nonrenewable groundwater abstraction, because it consists of additional water gained by groundwater abstraction in surplus of groundwater recharge. Groundwater can serve as a temporary source of irrigation water if during the dry season or during dry years surface water is insufficient to satisfy demand. Also, groundwater may be the main source of irrigation water in areas overlying productive aquifers wherever access to surface water is limited. Importantly, as long as abstraction is smaller than recharge, it will only reduce the groundwater discharge to surface water (base flow) and as such can be counted as available blue water. However, if groundwater abstraction exceeds the groundwater recharge over extensive areas for prolonged periods, persistent groundwater depletion occurs [*Gleeson et al.*, 2010] where groundwater reserves still exist, leading to falling groundwater levels [*Konikow and Kendy*, 2005; *Karami and Hayati*, 2005; *Reilly et al.*, 2008; *Rodell et al.*, 2009; *Tiwari et al.*, 2009; *McGuire*, 2009; *Scanlon et al.*, 2010; *Famiglietti et al.*, 2011]. In that case fossil groundwater, not being an active part of the current hydrological cycle, is used as an additional, albeit nonrenewable, source of irrigation water.

[4] Previous studies by *Vörösmarty et al.* [2005], *Rost et al.* [2008], *Wisser et al.* [2010], and *Hanasaki et al.* [2010] implicitly quantified the amount of nonrenewable and nonlocal water resources on the basis of the amount of water demand exceeding locally accessible supplies of blue water. However, uncertainties of these estimates inherently remain large (389–1199 km^3 yr^{-1}) since they are sensitive

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to both estimated water demand (1206–3557 km^3 yr^{-1}) and simulated surface freshwater availability (i.e., water in rivers, lakes, and reservoirs; 36,921–41,820 km^3 yr^{-1}).

[5] At the same time, estimated groundwater abstraction ranges globally between 600 and 1100 km^3 yr^{-1} [*Shah et al.*, 2000; *Zektser and Everett*, 2004; *Döll*, 2009; *Wada et al.*, 2010]. Recently, using a forward modeling approach, *Siebert et al.* [2010] quantified the amount of groundwater consumed through current irrigation practice to be 545 km^3 yr^{-1}. Yet, up to now, all global studies dealing with sources of irrigation water demand have not explicitly identified which part of the irrigation water demand is currently met from *nonrenewable* groundwater abstraction. Regional studies by *Rodell et al.* [2009], *Tiwari et al.* [2009], and *Famiglietti et al.* [2011] using the Gravity Recovery and Climate Experiment (GRACE) [*Tapley et al.*, 2004] satellite observation revealed that considerable amounts of nonrenewable groundwater resources are being abstracted in northeast India and northwest Pakistan and California's Central Valley in the United States, most of which is used for irrigation. *McGuire* [2009] and *Scanlon et al.* [2010] also reported depleting groundwater resources because of irrigation in the High Plains (Ogallala) aquifer, United States. It can thus be expected that large amounts of nonrenewable groundwater are indeed abstracted for irrigation purposes, particularly during the growing season when irrigation water demand exceeds available surface freshwater resources. Assessing globally this contribution is important because it pinpoints areas where irrigation and thus food production is sustained by a nonsustainable water resource.

[6] In this paper, expanding on existing studies, we explicitly quantify the amount of nonrenewable or nonsustainable groundwater abstraction used for current irrigation practice at the global scale. In order to make use of the best available data and to make our assessment as relevant for the present-day situation as possible, we opted for the year 2000. The trend of past groundwater abstraction is reconstructed over the period 1960–2000 to highlight the increasing importance of nonrenewable groundwater abstraction in irrigation practice over the recent past when irrigated areas expanded rapidly. We provide a global total estimate only for the past period because of larger uncertainties caused by assumptions to overcome a lack of historical data set.

[7] This study follows an improved method to compute nonrenewable groundwater abstraction compared to that of *Wada et al.* [2010, 2011a]. Compared to these previous works we develop a new approach when downscaling country-based data on groundwater abstraction to grid-based estimates, while we additionally account for additional recharge that occurs from irrigation. We then focus on irrigated areas since the contribution of nonrenewable groundwater abstraction to irrigation has not been estimated by any of the previous work. Also, we add a reconstruction of the increased irrigation water demand from 1960–2000, as well as the contribution of other water resources available to meet crop water demand such as soil moisture (green water) and surface freshwater (blue water).

[8] Green water and blue water availability are obtained from simulation with the global hydrological model PCR-Global Water Balance (PCR-GLOBWB) [*Van Beek et al.*, 2011] at a spatial resolution of 0.5° × 0.5° (i.e., 50 km × 50 km at the equator). Nonrenewable groundwater abstraction for irrigation is calculated by taking abstraction in excess of recharge, while considering the fraction of irrigation water demand over net total water demand. We subsequently compare the amount of nonrenewable groundwater abstraction used for irrigated crops to the amount of green water and blue water used for irrigation. It can be expected that the total amount of available green water and blue water and nonrenewable groundwater is insufficient to satisfy crop water demand since we simulate optimal crop growth. This shortage can be partly supplied from nonlocal water resources [cf. *Rost et al.*, 2008; *Hanasaki et al.*, 2010] such as desalination and diverting water ways (i.e., aqueducts). Again, assuming that optimal crop growth is aimed for, we equate this shortage with the additional supply from "nonlocal water resources" to be consistent with the previous studies. By explicitly defining the contribution of nonrenewable groundwater we can better confine previous assessments of "nonrenewable and nonlocal water resources" estimated by *Vörösmarty et al.* [2005], *Rost et al.* [2008], *Wisser et al.* [2010], and *Hanasaki et al.* [2010] and identify regions where irrigation is dependent on nonrenewable groundwater rather than surface freshwater or blue water.

2. Methodology

[9] We start section 2 by defining the various terms used to calculate nonrenewable groundwater abstraction, water demand and water availability. Next, we describe the calculation of water availability, irrigation water demand and the estimation of nonrenewable groundwater abstraction.

2.1. Definitions

[10] In this study, the term "nonrenewable groundwater" denotes groundwater gained by abstraction in excess of recharge for any region of the world, while the term "groundwater depletion" is used to denote persistent removal of groundwater from storage, which we estimate as overdraft restricted to subhumid to arid areas as done by *Wada et al.* [2010].

[11] Throughout the paper we will consistently use the term water "demand" to denote the need or requirement for water. The term demand is used to indicate that we can only estimate potential use, i.e., the water that would be used by a given activity if sufficient water were available. Water demand generally comes from three sectors: domestic water demand, industrial water demand and agricultural water demand. The latter can be further subdivided into irrigation water demand (by far the largest part) and livestock water demand. Environmental flow requirements are not accounted for in this study. In many analyses [e.g., *Döll and Siebert*, 2002; *Wisser et al.*, 2008; *Wada et al.*, 2011a] one distinguishes gross demand (including losses and return flows) from net demand (without losses and return flows). The latter is sometimes equated with consumptive water use [e.g., *Döll and Siebert*, 2002].

[12] Limiting ourselves to irrigation water demand we will use the following definitions.

[13] 1. Net crop water demand is the amount of water that is required to ensure maximum crop growth. Net crop water demand, $D_{C_{Net}}$ (m d^{-1}), is taken equal to crop-specific

potential evapotranspiration, which in turn can be related to reference evapotranspiration:

$$D_{C_{Net}} = \mathrm{ET}_c = k_c \mathrm{ET}_0 = (T_c + \mathrm{ES}_c), \quad (1)$$

where ET_c is the crop-specific evapotranspiration and ET_0 is the reference evapotranspiration (m d^{-1}). k_c is a dimensionless crop factor. T_c is the crop-specific potential transpiration, and ES_c is the potential bare soil evaporation over the irrigated areas (m d^{-1}). We chose to count soil evaporation as part of the net crop water demand as it plays a relatively large role in the early stages of crop development and equally uses soil moisture as does transpiration.

[14] 2. Net irrigation water demand is the amount of water, without counting transport and application losses, that needs to be supplied by irrigation to ensure maximum crop growth. If local precipitation is not sufficient to satisfy crop water demand, actual evapotranspiration falls below the potential rate. Thus, net irrigation water demand, $D_{I_{Net}}$ (m d^{-1}), is the amount of water that needs to be additionally supplied by irrigation to ensure maximum evapotranspiration:

$$D_{I_{Net}} = (T_c - T_a) + (\mathrm{ES}_c - \mathrm{ES}_a), \quad (2)$$

where T_a is the crop-specific actual transpiration and ES_a is the actual bare soil evaporation (m d^{-1}) that would occur over the irrigated areas in case no irrigation were present.

[15] 3. Green water is the actual evapotranspiration $T_a + \mathrm{ES}_a$ that would have occurred without irrigation. This is plant-available water stored in the soil that originates from local precipitation. We will use $\mathrm{Green_W}$ to denote green water.

[16] 4. Gross irrigation water demand is the amount of water, including transport and application losses, that needs to be supplied by irrigation to ensure maximum crop growth. Such losses include evaporative and percolation losses during transport from source to field and during application. Note that application-related evaporative losses are those that occur before irrigation water is able to infiltrate into the soil, i.e., interception evaporation and open water evaporation when flooding occurs, while percolation losses during irrigation are often induced to avoid topsoil salinity. Here gross irrigation water demand is calculated by multiplying the net irrigation water demand with a dimensionless country-specific efficiency factor, e_{Irr}:

$$D_{I_{Gross}} = e_{Irr} D_{I_{Net}}. \quad (3)$$

The efficiency factor increases the amount of irrigation water by about 10% to 40%. The country-specific efficiency factors were taken from *Rohwer et al.* [2007].

[17] 5. Gross crop water demand is the amount of water that is required to ensure maximum crop growth in irrigated areas, including applied irrigation water and losses through transport and application. We will denote this quantity by $D_{C_{Gross}}$.

[18] Gross irrigation water demand is then satisfied from available blue water, $\mathrm{Blue_W}$, nonrenewable groundwater, $\mathrm{NRGround_W}$, and potential nonlocal water resources, $\mathrm{NonL_W}$:

$$D_{I_{Gross}} = \mathrm{Blue_W} + \mathrm{NRGround_W} + \mathrm{NonL_W}, \quad (4)$$

while gross crop water demand can be supplied from four possible sources:

$$D_{C_{Gross}} = \mathrm{Green_W} + D_{I_{Gross}} = \mathrm{Green_W} + \mathrm{Blue_W} + \mathrm{NRGround_W} + \mathrm{NonL_W}. \quad (5)$$

2.2. Simulating Available Blue Water

[19] To estimate the amount of blue water available to satisfy gross irrigation water demand, we use the global hydrological model PCR-GLOBWB to simulate surface freshwater or water in rivers, lakes, reservoirs and wetlands [*Van Beek and Bierkens*, 2009]. We refer to *Van Beek et al.* [2011] for an extensive description. PCR-GLOBWB is a conceptual, process-based water balance model of the terrestrial part of the hydrological cycle except Antarctica. It simulates for each grid cell (0.5° × 0.5° globally) and for each time step (daily) the water storage in two vertically stacked soil layers and an underlying groundwater layer, as well as the water exchange between the layers and between the top layer and the atmosphere (rainfall, evaporation and snow melt). The model also calculates canopy interception and snow storage. Subgrid variability is taken into account by considering separately tall and short vegetation, open water (i.e., lakes, reservoirs, floodplains and wetlands), different soil types (Food and Agricultural Organization (FAO) Digital Soil Map of the World; http://www.fao.org/nr/land/soils/digital-soil-map-of-the-world), and the area fraction of saturated soil (improved ARNO scheme from *Hagemann and Gates* [2003]) as well as the frequency distribution of groundwater depth based on the surface elevations of the 1 × 1 km Hydro1k data set. Fluxes between the lower soil reservoir and the groundwater reservoir are mostly downward, except for areas with shallow groundwater tables, where fluxes from the groundwater reservoir to the soil reservoirs are possible (i.e., capillary rise) during periods of low soil moisture content. The total specific runoff of a cell consists of saturation excess surface runoff, melt water that does not infiltrate, runoff from the second soil reservoir (interflow) and groundwater runoff (base flow) from the lowest reservoir.

[20] Simulated specific runoff from the two soil layers (i.e., direct runoff and interflow) and the underlying groundwater layer (i.e., base flow) is routed along the drainage network on the basis of DDM30 [*Döll and Lehner*, 2002] by using the kinematic wave approximation of the Saint-Venant equation [*Chow et al.*, 1988]. The effect of open water evaporation, storage changes by lakes, attenuation by floodplains and wetlands, and reservoir operations (i.e., water supply, flood control, hydropower and navigation) are taken into account as well [*Van Beek et al.*, 2011].

[21] In this study, PCR-GLOBWB was forced with daily fields of precipitation, reference evapotranspiration and temperature over the period 1958 to 2001. Precipitation and air temperature were prescribed by the Climate Research Unit (CRU) TS 2.1 monthly data set [*Mitchell and Jones*, 2005; *New et al.*, 2000] which was subsequently downscaled to the daily fields [*Van Beek et al.*, 2011] by using the ERA40 reanalysis data [*Uppala et al.*, 2005]. Although the Climate Research Unit (CRU) TS 2.1 underestimates precipitation because of snow undercatch [*Fiedler and Döll*, 2007] over the Arctic regions, this weakness is of little consequence for

this study as no major irrigated areas are located there. Prescribed reference evapotranspiration was calculated on the basis of the Penman-Monteith equation according to the FAO guidelines [*Allen et al.*, 1998] by using time series data of CRU TS 2.1 with additional inputs of radiation and wind speed from the CRU CLIM 1.0 climatology data set [*New et al.*, 2002]. Crop-specific potential evapotranspiration was obtained from a crop factor climatology per grid cell derived from combining land cover data (GLCC version 2; U.S. Geological Survey's (USGS) Earth Resources Observation and Science Center, Global land cover characteristics data base version 2.0, http://edc2.usgs.gov/glcc/glcc. php), data on leaf area index (LAI) values at dormancy and peak of the growing season [*Hagemann et al.*, 1999] and the monthly CRU climatology of temperature, precipitation, and potential evapotranspiration over 1961–1990 (see *Van Beek et al.* [2011] for details).

[22] PCR-GLOBWB is run with a daily time step but blue water availability is subsequently evaluated at monthly time steps. Local blue water availability at a given time and for a given cell i is finally obtained by taking the cumulative discharge along the river network (including lakes, wetlands and reservoirs that are part of the drainage network) after subtracting upstream net total water demand, $D_{T_{Net}}$, which is the sum of blue water demand of all sectors (domestic, industrial and agricultural sector) after subtracting return flows:

$$\mathrm{WA} = Q_{Loc,i} + \sum_{j=i+1}^{n} (Q_j - D_{T_{Net},j}), \tag{6}$$

where WA is blue water availability, Q_{Loc}, is the specific discharge or local runoff in cell i, $D_{T_{Net}}$ is the net total water demand of upstream cell j (all in m^3 d^{-1}), taken to be the local water consumption [*Döll and Siebert*, 2002], and $j = i + 1 \ldots n$, all upstream the cells draining to cell i.

2.3. Estimating Green Water and Water Demand per Sector

[23] Although we focus on irrigation water demand, we need water demand for all sectors (domestic, industrial and agricultural including livestock sector), in order to calculate blue water availability (equation (6)) as well as to estimate groundwater abstraction at the scale of grid cells (see section 2.4). We will describe in brief how the various terms are calculated. For an extensive description of methods we refer to *Wada et al.* [2011a, 2011b].

[24] Agricultural water demand can be subdivided into livestock and irrigation water demand. As in previous studies [e.g., *Döll and Siebert*, 2002; *Rost et al.*, 2008; *Wisser et al.*, 2008; *Hanasaki et al.*, 2010], we combine gridded irrigated areas and crop-related data to estimate irrigation water demand. First, we took the map of irrigated areas based on the MIRCA2000 data set [*Portmann et al.*, 2010] and combined it with crop factors and growing season lengths from GCWM [*Siebert and Döll*, 2010]. Both data sets are representative for the year 2000. Using these as input to PCR-GLOBWB and forcing the model with precipitation and reference evapotranspiration data as described in section 2.2, this yielded daily time series of actual evapotranspiration, which can be seen as the evapotranspiration of the crops in the irrigated areas in case no irrigation was applied. This was used as an estimate of green water, Green$_\mathrm{W}$. Subtracting this amount from calculated time series of crop-specific potential evapotranspiration for the irrigated areas (net crop water demand, $D_{C_{Net}}$, equation (1)) then resulted in time series of net irrigation water demand, $D_{I_{Net}}$, (equation (2)). Multiplication with country-specific efficiency factors (equation (3)) from *Rohwer et al.* [2007] finally resulted in daily time series of gross irrigation water demand, $D_{I_{gross}}$. Daily time series were aggregated to monthly values before further analysis. As stated above, the data obtained are representative for the year 2000. To obtain monthly time series of Green$_\mathrm{W}$, $D_{I_{Net}}$ and $D_{I_{gross}}$ for the period of interest 1960–2000 we repeated this procedure for each year, while estimating the growth of irrigated areas by combining country-specific statistics on irrigated areas (FAOSTAT; http://faostat.org/) with the MIRCA 2000 data set [*Portmann et al.*, 2010] (see *Wisser et al.* [2010] and *Wada et al.* [2011b] for details).

[25] Livestock water demand from 1960–2000 was reconstructed on the basis of statistics of livestock densities [*Wint and Robinson*, 2007; FAOSTAT, http://faostat.org/], while industrial and domestic water demand over the same period could be estimated using statistics on population and socioeconomic drivers (e.g., GDP and electricity production) taken from the FAOSTAT, the UNEP (http://www.unep.org/) and the World Bank (http://www.worldbank.org/). To calculate return flows needed to estimate net water demand (i.e., potential consumptive water use), we used country-specific recycling ratios calculated by *Wada et al.* [2011a] on the basis of economic development stages. We refer to *Wada et al.* [2011a] for details on these calculations. Adding industrial and domestic water demand (after subtraction of return flows), livestock water demand and gross irrigation water demand yields net total water demand, $D_{T_{Net}}$.

2.4. Estimating Nonrenewable Groundwater Abstraction for Irrigation

[26] Nonrenewable groundwater abstraction in irrigated areas is obtained in three steps: (1) calculation of grid-based (0.5° × 0.5°) natural groundwater recharge and additional recharge from irrigation, (2) downscaling of country-based estimates on groundwater abstraction to grid-based groundwater abstraction, and (3) for the irrigated areas, subtracting grid-based groundwater abstraction from groundwater recharge to estimate nonrenewable groundwater abstraction for irrigation. Although groundwater depletion leads to increased capture of exogenous surface water and groundwater through a reduction of groundwater discharge to streams and increased recharge from streams [*Bredehoeft*, 2002], in many (semiarid) areas with extensive and long-time groundwater exploitation, with thousands of small agricultural wells dispersed over the entire groundwater region, the effects of increased capture are rather small or the time of increased capture has long passed, and removal from storage can be estimated by the difference between abstraction and recharge rates [*Wada et al.*, 2010]. In sections 2.4.1–2.4.3 these three steps are subsequently described in more detail.

2.4.1. Natural Groundwater Recharge and Additional Recharge From Irrigation

[27] Natural groundwater recharge can be readily obtained from the simulation of PCR-GLOBWB for the

period 1960–2000, where the natural groundwater recharge is estimated as the net flux from the lowest soil layer to the groundwater layer, i.e., deep percolation minus capillary rise. Note that in PCR-GLOBWB, the long-term average of groundwater recharge equals long-term average groundwater discharge from the groundwater layer to the surface water network. Our estimate of the average natural groundwater recharge globally amounts to 15.2×10^3 km^3 yr^{-1} [*Wada et al.*, 2010]. It should be noted that the simulated recharge does not explicitly include recharge from streams and lakes, although such effects may be implicitly included when calibrating soil characteristics to reproduce observed low-flow properties.

[28] To account for additional groundwater recharge from irrigation, R_{Irr}, we use the following approximation:

$$R_{Irr,i} = \min(L_{Irr,i}, k(\theta_{E\_FC,i})A_{Irr,i}), \tag{7}$$

where L_{Irr} is the amount of irrigation losses estimated on the basis of the country-specific efficiency factor e_{Irr} (as used in equation (3)) (m^3 d^{-1}), $k(\theta_{E\_FC})$ is the unsaturated hydraulic conductivity at field capacity (m d^{-1}) and A_{Irr} is the corresponding irrigated areas within the cell (m^2). This formulation is based on the fact that in irrigation practice water is supplied to wet the soil to field capacity during the application and the amount of irrigation water in excess of the field capacity can percolate to the groundwater system. The additional recharge rate thus equals the unsaturated hydraulic conductivity of the bottom soil layer at field capacity, assuming gravitational drainage. However, the total percolation losses are further constrained by the reported country-specific loss factor on the basis of the work by *Rohwer et al.* [2007].

2.4.2. Grid-Based Groundwater Abstraction for Irrigation

[29] To estimate grid-based groundwater abstraction, we start with groundwater abstraction rates per country and groundwater regions where major aquifers are present as stored in the IGRAC GGIS database (International Groundwater Resources Assessment Centre, http://www.un-igrac.org/). We indexed country-based groundwater abstraction to the year 2000 on the basis of population statistics as most abstraction data are collected before the year 2000. Data on abstraction rates were lacking for Afghanistan, North Korea, Sri Lanka, Colombia, and several countries in Africa and South America.

[30] Since the locations where groundwater is abstracted by wells are not known for most of the countries, *Wada et al.* [2010] downscaled groundwater abstraction per country to a 0.5° grid resolution by using water demand as a proxy, i.e., on the basis of the assumption that groundwater is abstracted close to where it is most needed. In this study, we improve on their approach by taking into account the available surface freshwater.

[31] First, for each month, m, in the year 2000 and for each grid cell, i, we calculate deficits, $\mathrm{Defs}_{m,i}$, between the surface water availability, $\mathrm{WA}_{m,i}$, simulated by PCR-GLOBWB (after correcting for upstream water consumption through equation (6)) and the estimated net total water demand, $D_{T_{Net}m,i}$ (see section 2.3). Because we are interested in groundwater as an alternative source we limit this analysis to regions where the aquifers are present (major groundwater regions of the world according to the IGRAC GGIS). We subsequently estimate annual deficits, $\mathrm{Defs}_{a,i}$, for the year 2000.

$$\mathrm{Defs}_{a,i} = \sum_{m=1}^{12} \mathrm{Defs}_{m,i} = \sum_{m=1}^{12} (D_{T_{Net}m,i} - \mathrm{WA}_{m,i}). \tag{8}$$

We assume that grid cells with deficits (i.e., water demand in excess of blue water availability) are the main locations where groundwater is abstracted as an alternative resource to satisfy the demand.

[32] Second, the annual deficits, $\mathrm{Defs}_{a,i}$, are filled by the amount of available country total groundwater abstraction until total water demand is satisfied by groundwater abstraction per grid cell. Total annual deficits per country, Defs_a, are given by

$$\mathrm{Defs}_a = \sum_{i=1}^{n} \mathrm{Defs}_{a,i}, \tag{9}$$

where n is the number of grid cells with deficits per country. If the total annual deficits are larger than the available annual groundwater abstraction in a country, $\mathrm{Defs}_a > \mathrm{Ground}_{\mathrm{W}a}$, (e.g., Egypt, Sudan, Mali, Niger, Sudan, Turkmenistan and Uzbekistan), we distribute the country abstraction according to the intensities rather than the volume of the deficits. In most cases the available abstraction is larger than the total deficits in a country and the remaining country-based abstraction ($\mathrm{Ground}_{\mathrm{W}a} - \mathrm{Defs}_a$) is further allocated relative to the intensity of total water demand over its country total (again limited to cells in major groundwater regions):

$$\mathrm{Ground}_{\mathrm{W}a,i} = \mathrm{Defs}_a + (\mathrm{Ground}_{\mathrm{W}a} - \mathrm{Defs}_a) \frac{D_{T_{Net}a,i}}{\sum_{i=1}^{n} D_{T_{Net}a,i}}. \tag{10}$$

[33] Third, we use the fraction of irrigation water demand over net total water demand in each grid cell in the irrigated areas to arrive at groundwater abstraction for irrigation, $\mathrm{Ground}_{\mathrm{W},Irra,i}$:

$$\mathrm{Ground}_{\mathrm{W},Irra,i} = \frac{D_{I_{Gross}}}{D_{T_{Net}}} \mathrm{Ground}_{\mathrm{W}a,i}. \tag{11}$$

Over the irrigated areas (MIRCA2000 [*Portmann et al.*, 2010]) irrigation water demand is dominant, so that groundwater abstraction for irrigation is close to the total groundwater abstraction in irrigated areas.

2.4.3. Nonrenewable Groundwater Abstraction for Irrigation

[34] Nonrenewable groundwater abstraction is subsequently calculated by subtracting the sum of the simulated natural groundwater recharge and additional recharge from irrigation from the gridded groundwater abstraction in a vertical slice per grid cell over all regions of the world. Negative values indicate grid cells with overlaps between available blue water and renewable groundwater abstraction

and the remaining positive values denote grid cells where nonrenewable groundwater is abstracted. Nonrenewable groundwater abstraction for irrigation is estimated again by using the fraction of irrigation water demand over net total water demand in each grid cell in the irrigated areas:

$$\mathrm{NRGround}_{\mathrm{W},Irra,i} = \frac{D_{I_{Gross}}}{D_{T_{Net}}} \mathrm{NRGround}_{\mathrm{W}a,i}. \quad (12)$$

[35] We also assessed the past trend of groundwater abstraction for the period 1960–2000 as a first-order estimate assuming that country-based groundwater abstraction increases linearly with water demand. So for a given year, *k*, an estimate of country-based groundwater abstraction is obtained by multiplying the groundwater abstraction of the year 2000 by the ratio of country-based water demand of year, *k*, over that of the year 2000 water demand. Water demand is calculated according to *Wada et al.* [2011a, 2011b] (see section 2.3). Next, by repeating for each year the methodology previously described, we thus estimate the amount of nonrenewable groundwater abstraction for irrigation during the period 1960–2000.

3. Results

3.1. Model Evaluation and Validation

[36] Before we present the result of nonrenewable groundwater for irrigation, we first provide the evaluation of model performance and validation result for downscaling country total groundwater abstraction rates to 0.5° grids, and compare estimated nonrenewable groundwater abstraction to independent estimates of groundwater depletion.

[37] To assess model performance, we compared simulated terrestrial water storage (TWS) to the GRACE satellite observations. Monthly GRACE TWS anomalies were obtained from the DEOS Mass Transport release 1/1b (DMT-1) model of *Liu et al.* [2010] for the period 2003–2008. Since this period extends beyond that of the available climate forcing for PCR-GLOBWB used in this study (section 2.2), we forced the model by a comparable climate data set of daily rainfall and temperature fields taken from the ECMWF Operational Archive (http://www.ecmwf.int/products/data/archive/descriptions/od/oper/index.html). For compatibility with our overall analysis, we bias-corrected this data set by scaling the long-term monthly means of these fields to those of the CRU TS 2.1 data set. Monthly reference (potential) evapotranspiration was computed according to the FAO guidelines [*Allen et al.*, 1998] using the relevant long-term monthly values from the CRU TS 2.1 and CLIM 1.0 data sets (section 2.2) where temperature was replaced by that of the bias-corrected ECMWF Operational Archive, and subsequently downscaled on the basis of the daily temperature. Figure 1 compares our simulated TWS anomalies with those of the GRACE observations for major basins of the world. PCR-GLOBWB reproduces the seasonal and interannual variations in TWS well particularly in (semi)arid basins such as Niger and Zambezi. TWS is also reproduced reasonably well for basins where major irrigated areas are present such as Mississippi, Nile, Indus, Genges and Mekong. However, PCR-GLOBWB underestimates TWS for most of the period for Yangtze. This might be caused by overestimation of our evapotranspiration, resulting in underestimation of soil water storage and surface runoff. For Danube, TWS is underestimated for 2006 in which significant flooding, i.e., 2006 European floods, occurred because of heavy rain and melting snow, while it is well reproduced for the other years. Overall, PCR-GLOBWB reproduces TWS adequately for most of the basins, which increases our confidence on model performance.

[38] Figure 2 compares our estimated groundwater abstraction rates for the United States with reported values per county taken from the USGS (http://www.usgs.gov/). Both estimated and reported values sum up to a total of around 115 km^3 yr^{-1} (year 2000). Although the spatial resolution does not exactly correspond with each other, our estimated groundwater abstraction rates show a good agreement with those of the USGS throughout the United States (excluding Alaska and Hawaii). Large groundwater abstraction rates over the High Plains (Ogallala) Aquifer, the Central Valley, California, the Mississippi River Valley alluvial aquifer, the Basin and Range basin fill aquifers, Florida, the Pacific Northwest basaltic rock aquifers and the Snake River Plain basaltic rock aquifers are well reproduced by our downscaling method (see section 2.4.2). For the Southwest, we also have a good agreement if we add up our downscaled values per county.

[39] Table 1 shows, per country, our estimate of nonrenewable groundwater abstraction rates. An uncertainty analysis for the estimates was performed according to *Wada et al.* [2010]. Note that here we use estimates of total nonrenewable groundwater abstraction for all purposes including irrigation as an estimate of groundwater depletion, i.e., groundwater removal from storage. Moreover, we limit our estimates to subhumid to arid regions to prevent excessive overestimation of groundwater depletion due to enhanced recharge as would occur in areas with abundant surface water. Comparing to the previous works by *Wada et al.* [2010, 2011a], we rectified the groundwater recharge estimate by including additional recharge from irrigation to find that global recharge is enhanced by 420 km^3 yr^{-1} which reduces depletion from 283 ($\pm$40) to 256 ($\pm$38) km^3 yr^{-1}. Figure 3 compares for several regions our estimates of groundwater depletion rates with independent estimates of groundwater depletion [*Sahagian et al.*, 1994; *McGuire*, 2003; *Foster and Loucks*, 2006; *Rodell et al.*, 2009; *Tiwari et al.*, 2009; *Famiglietti et al.*, 2011; *Konikow*, 2011]. As shown in Figure 3, our estimates compare well with the other independent assessments of groundwater depletion reported around the year 2000, showing that our approach does not lead to large structural errors. The exception here is the estimate for north India (i.e., Rajasthan, Punjab, Haryana) and northern India and adjacent areas (NIAAs) where compared to the GRACE estimates from *Rodell et al.* [2009] and *Tiwari et al.* [2009], groundwater depletion is overestimated (38.3 km^3 yr^{-1} versus 17.7 km^3 yr^{-1} and 71.7 km^3 yr^{-1} versus 54 km^3 yr^{-1}). This most likely results from the fact that surface water availability necessary to meet the large irrigation water demand is underestimated as it is known that in the Indo-Gangetic plains extensive diversion works are present [*Sharma and Kansal*, 2009] that are not included in our modeled surface water system. Also, it may well be that additional recharge occurs from these diversions.

[40] A comparison of our estimates with those of a recent study by *Konikow* [2011] also shows a reasonable

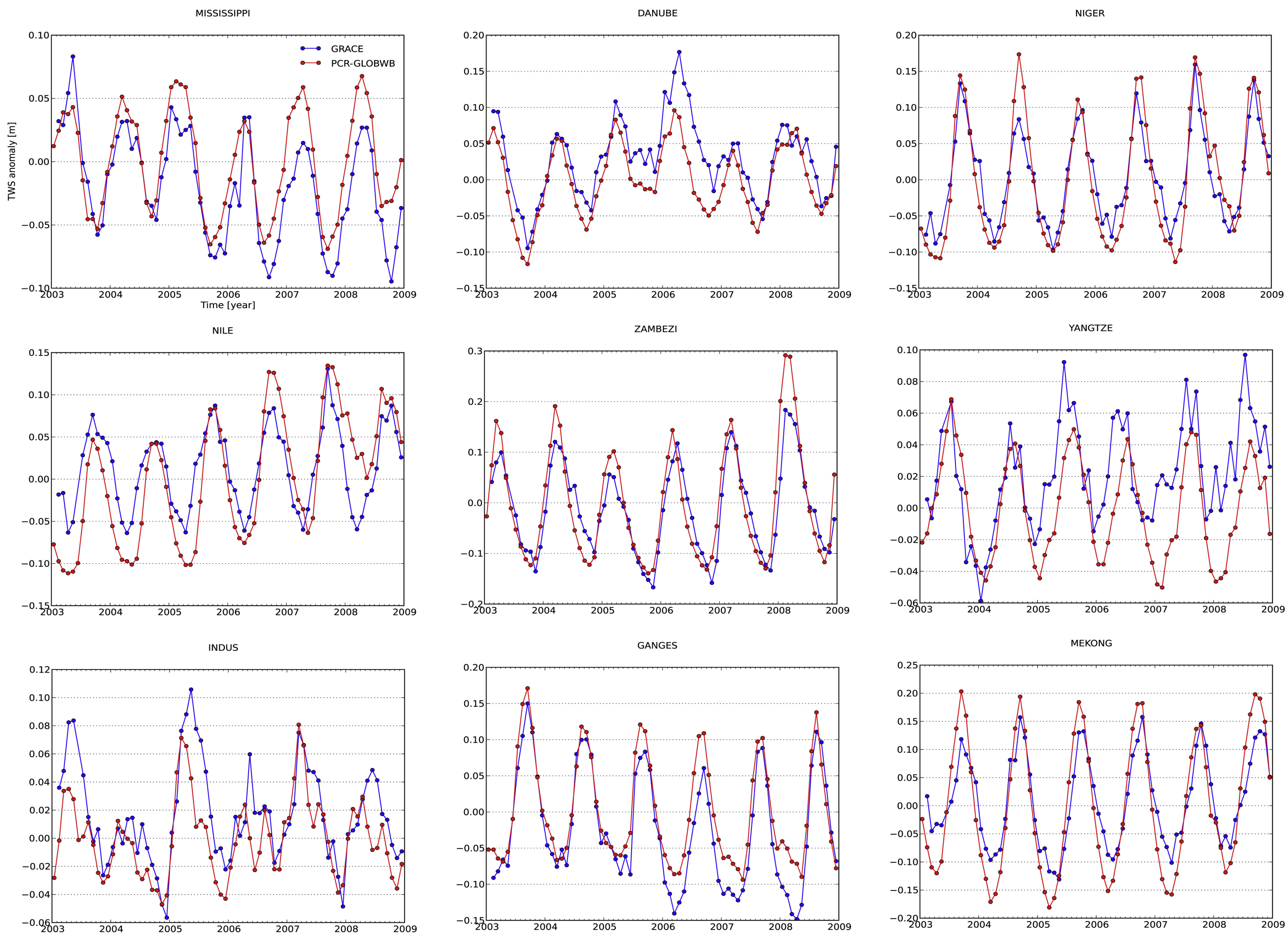

Figure 1. Comparison of simulated monthly terrestrial water storage anomalies (y axis, m) with those of the Gravity Recovery and Climate Experiment (GRACE) observations for major basins of the world during the period 2003–2008. Blue and red line indicates the GRACE observation and PCR-GLOBWB simulation, respectively. Monthly GRACE terrestrial water storage anomaly data were obtained from the DEOS Mass Transport release 1/1b (DMT-1) model [*Liu et al.*, 2010]. The data are not available for January and June 2003.

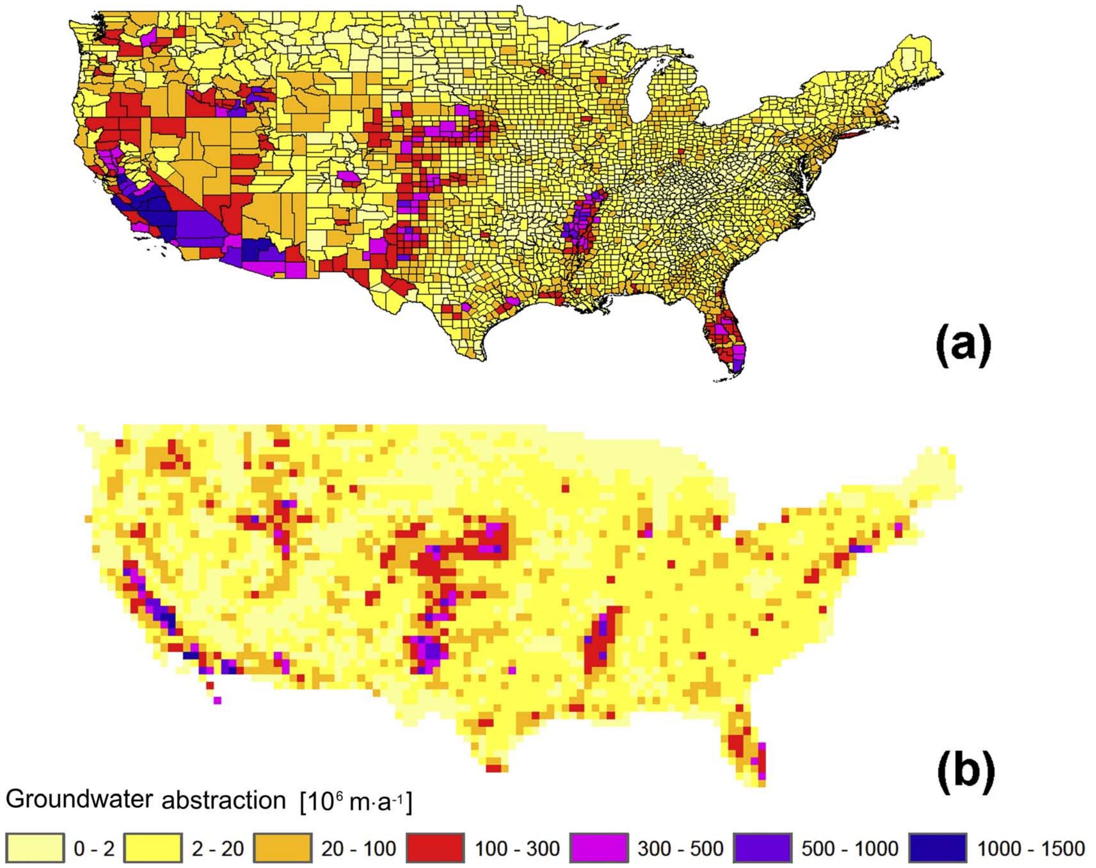

Figure 2. Groundwater abstraction rates in the United States (excluding Alaska and Hawaii), in 10^6 m^3 yr^{-1}, as (a) reported by the U.S. Geological Survey (http://www.usgs.gov/) per county in the year 2000 and (b) computed by this study at 0.5° for the year 2000.

agreement (see Figure 3). We compare our estimates with *Konikow*'s [2011] results for the last period 2000–2008 since these estimates are also closest to the other independent estimates. Differences between these estimates are relatively small, except for the estimate for northern India and adjacent areas, which *Konikow* [2011] equally takes from *Tiwari et al.* [2009] and one region in the United States: western U.S. alluvial basins. This region used to have depletion rates similar in magnitude to our estimate during the period 1950–1980, after which surface water diversions and artificial recharge programs reduced depletion to small values [*Konikow*, 2011]. If we add up the depletion rates from the United States and the other 5 regions evaluated by *Konikow* [2011], we end up with a depletion of 132.8 km^3 yr^{-1} which is not very different from the 101.6 km^3 yr^{-1}, given the uncertainty estimate provided for the global estimate (27% for *Konikow* [2011] and 38 km^3 yr^{-1} for this study). The global estimate of groundwater depletion by *Konikow* [2011] (145 km^3 yr^{-1}) is however very different from that of ours (256 km^3 yr^{-1}; see Table 1). This is largely due to the extrapolation performed by *Konikow* [2011] assuming that the ratio of depletion to groundwater abstraction of the rest of the world is the same as that of the United States (i.e., 15.4%). Table 1 shows that this is clearly not the case as the ratios considerably vary among countries (between 7% and 87%). For instance, taking the estimated depletion from the GRACE [*Tiwari et al.*, 2009] for northern India and adjacent areas (54 km^3 yr^{-1}) and comparing this to reported abstraction rates (see http://www.un-igrac.org/) for India (190 km^3 yr^{-1}) and Pakistan (55 km^3 yr^{-1}) already yields a ratio of 22% and could easily ad up to 25–30% if we correct the total abstraction of 245 km^3 yr^{-1} with the part that is abstracted in southern India. These fractions are much higher than the 15.4% assumed by *Konikow* [2011] and largely explain the differences between his and our estimates. Major other hotspots such as Iran, Mexico, the remaining parts of India and China and a number of countries in central Asia and the Middle East are thus not adequately accounted for by *Konikow* [2011].

3.2. Total and Nonrenewable Groundwater Abstraction for Irrigation

[41] Resulting groundwater abstraction for irrigation downscaled to 0.5° for the year 2000 is shown in Figure 4c, while Figure 4a shows the groundwater abstraction per country obtained from the IGRAC GGIS database and Figure 4b shows the estimated irrigation water demand. Figure 5 shows the estimated nonrenewable groundwater abstraction for irrigation for the year 2000. Large amounts of groundwater are being abstracted over major irrigated regions such as India, northern China, United States, Pakistan, southern Mexico, northern Iran, central Saudi Arabia, and southern Europe. Summing total and nonrenewable

Table 1. Reported Groundwater Abstraction Rate and Estimated Groundwater Depletion per Country With Ranges of Uncertainty for the Year 2000[a]

Country	Abstraction (A) ($km^3\ yr^{-1}$)	Depletion (D) ($km^3\ yr^{-1}$)	D/A (%)
India	190 (±37)	71 (±21)	37 (±19)
United States	115 (±14)	32 (±7)	28 (±9)
China	97 (±14)	22 (±5)	22 (±9)
Pakistan	55 (±17)	37 (±12)	69 (±48)
Iran	53 (±10)	27 (±8)	52 (±24)
Mexico	38 (±4)	11 (±3)	30 (±11)
Saudi Arabia	21 (±3)	15 (±4)	72 (±30)
Russia	12 (±2)	1.5 (±0.5)	14 (±7)
Italy	11 (±3)	2.3 (±0.6)	21 (±13)
Turkey	8 (±2)	2.4 (±0.8)	31 (±18)
Uzbekistan	6.5 (±1.8)	4.0 (±1.4)	63 (±43)
Egypt	5 (±1.3)	3.0 (±1.2)	61 (±43)
Bulgaria	4.8 (±1.4)	2.0 (±0.8)	42 (±32)
Spain	4.6 (±1.1)	1.7 (±0.6)	37 (±23)
Argentina	4.5 (±0.9)	0.9 (±0.3)	20 (±11)
Libya	4.4 (±1.2)	3.1 (±0.9)	70 (±43)
Ukraine	4.2 (±0.9)	0.3 (±0.08)	7 (±3.5)
Romania	3.5 (±1)	1.3 (±0.6)	38 (±30)
Kazakhstan	3.4 (±1)	2.0 (±0.5)	59 (±35)
South Africa	3.0 (±0.7)	1.5 (±0.5)	50 (±30)
Algeria	2.5 (±0.7)	1.7 (±0.6)	69 (±48)
Greece	2.4 (±0.6)	0.34 (±0.1)	14 (±8)
Morocco	2.4 (±0.4)	1.6 (±0.5)	67 (±34)
Australia	2.1 (±0.4)	1.0 (±0.3)	48 (±24)
Tajikistan	1.9 (±0.5)	1.2 (±0.4)	61(±40)
Yemen	1.9 (±0.5)	0.9 (±0.3)	49 (±31)
Turkmenistan	1.85 (±0.5)	1.25 (±0.5)	70 (±50)
Syria	1.59 (±0.4)	1.23 (±0.3)	78 (±41)
UAE	1.55 (±0.3)	1.18 (±0.4)	76 (±42)
Tunisia	1.55 (±0.5)	0.65 (±0.2)	42 (±30)
Peru	1.23 (±0.4)	0.32 (±0.08)	26 (±17)
Bolivia	0.68 (±0.2)	0.25 (±0.08)	37 (±25)
Israel	0.61 (±0.2)	0.38 (±0.1)	62 (±41)
Kyrgyzstan	0.61 (±0.2)	0.31 (±0.1)	51 (±37)
Jordan	0.52 (±0.2)	0.22 (±0.08)	42 (±38)
Mauritania	0.51 (±0.1)	0.36 (±0.1)	71 (±35)
Oman	0.50 (±0.2)	0.20 (±0.06)	39 (±33)
Kuwait	0.29 (±0.1)	0.25 (±0.09)	87 (±70)
Qatar	0.18 (±0.05)	0.15 (±0.06)	83 (±60)
Globe	734 (±82)	256 (±38)	34 (±9)

[a]See the International Groundwater Resources Assessment Centre (http://www.un-igrac.org/) for abstraction rate. An uncertainty analysis was performed according to *Wada et al.* [2010]. D/A denotes the fraction of depletion over abstraction (%). Groundwater depletion was estimated by the nonrenewable groundwater abstraction for subhumid to arid areas in each country [cf. *Wada et al.*, 2010].

groundwater abstraction for irrigation for these areas amounts to 80% and 90% of the global total for the year 2000, respectively.

3.3. Contribution of Water (Re)sources to Irrigated Crops

[42] On the basis of the simulations with PCR-GLOBWB and the calculations of water demand and nonrenewable groundwater abstraction we estimated the contribution of different sources of water to irrigated crops, i.e., to gross crop water demand: green water, blue water, nonrenewable groundwater or nonlocal water resources. For the year 2000, water used for irrigated crops globally amounts to 2510 $km^3\ yr^{-1}$, of which 47% (1172 $km^3\ yr^{-1}$) and 53% (1338 $km^3\ yr^{-1}$) are composed of green water use and gross irrigation water demand, respectively (see Table 2). Blue water contributes 63% or 844 $km^3\ yr^{-1}$ to the gross irrigation water demand while nonrenewable groundwater contributes 18% or 234 $km^3\ yr^{-1}$. Potential nonlocal water resources contribute the remaining 19% or 260 $km^3\ yr^{-1}$ to the gross irrigation water demand. We estimate that about 85% of the global nonrenewable groundwater abstraction (275 $km^3\ yr^{-1}$) is used for irrigation. Our estimate of nonrenewable groundwater used for irrigated crops is comparable to the lower range of that of *Vörösmarty et al.* [2005], who suggest that 16% to 33% of agricultural water demand is nonlocal and nonrenewable (391 to 830 $km^3\ yr^{-1}$). If we add our estimate of nonrenewable groundwater abstraction to that of nonlocal water resources, being the remaining shortage to bring irrigation water to the optimum, our total falls within their range.

[43] Focusing on country estimates in Table 2, it can be seen that India needs the amount of 600 $km^3\ yr^{-1}$ of water in order to satisfy its gross crop water demand in irrigated areas, which is nearly a quarter of the global total. In India, the gross irrigation water demand (353 $km^3\ yr^{-1}$) constitutes nearly 60% of its gross crop water demand, of which 19%, or 68 $km^3\ yr^{-1}$, is supplied from nonrenewable groundwater. India uses the largest amount of nonrenewable groundwater for irrigation among the countries. Because of the scarce rainfall under its semiarid climate, in Pakistan most (80%, or 146 $km^3\ yr^{-1}$) of the gross crop water demand is satisfied by irrigation. While a major part of the irrigation water is taken from the Indus river, nonrenewable groundwater contributes 24% to the gross irrigation water demand and amounts to 35 $km^3\ yr^{-1}$, the second largest volume after India. Similar to India, gross irrigation water demand constitutes 60% of the gross crop water demand of the United States and Mexico. In these countries, around 20% of gross irrigation water demand comes from nonrenewable groundwater while around 60% is supplied from blue water. In Iran and Saudi Arabia, where rainfall and surface freshwater are extremely scarce, nonrenewable groundwater provides the largest contribution to gross irrigation water demand, 40% and 77%, respectively. Our estimate in Saudi Arabia suggests that its irrigation practice is near-optimal in terms of productivity and sustained by the large abstraction of nonrenewable groundwater resources. In China, on the other hand, nonrenewable groundwater contributes merely around 15% to the gross irrigation water demand. This can be explained by the large share of green water used by irrigated crops which enjoy substantial but variable rainfall, contributing 66%, or 267 $km^3\ yr^{-1}$, to the gross crop water demand, the largest volume for any of the major irrigated countries.

[44] Figure 6 shows the current contribution of each water resource to irrigated crops (gross crop water demand in irrigated areas) for major groundwater users such as India, China, United States, Pakistan, Iran, Mexico, Saudi Arabia, Egypt, Spain and Libya. Large fractions of nonrenewable groundwater abstraction over gross irrigation water demand are observed predominantly in arid regions such as the Middle East. Nonrenewable groundwater supplies more than half of the gross irrigation water demand in Saudi Arabia, Qatar, Libya and UAE. However, it should be noted that gross crop water demand in most of countries is not fully covered by the sum of available green water, blue water and nonrenewable groundwater, particularly in water scarce regions such as India, United States, Pakistan, Iran,

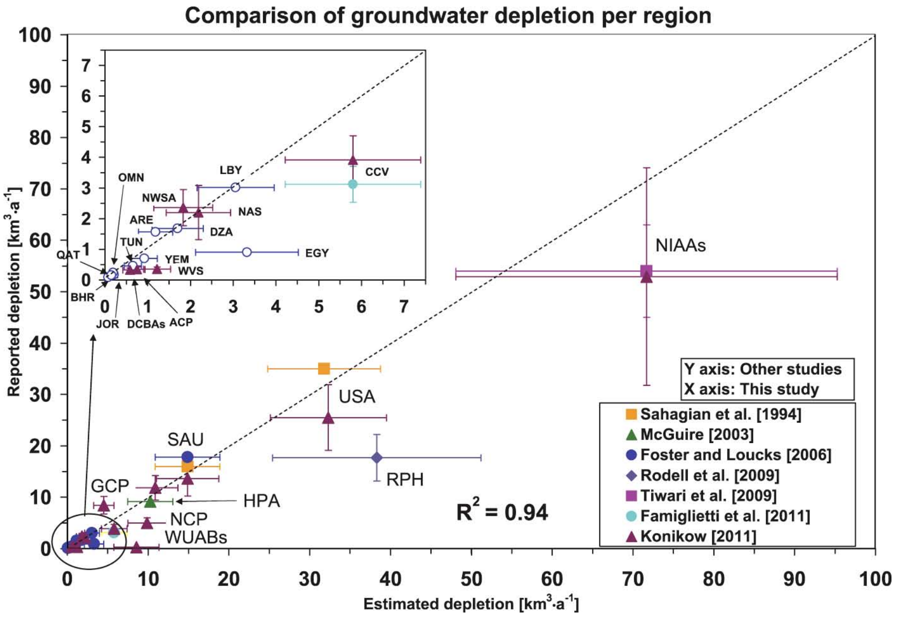

Figure 3. Comparison estimates of groundwater depletion rates between this study and independent estimates taken from *Sahagian et al.* [1994], *McGuire* [2003], *Foster and Loucks* [2006], *Rodell et al.* [2009], *Tiwari et al.* [2009], *Famiglietti et al.* [2011], and *Konikow* [2011]. Countries are identified by their ISO country codes. The dashed lines represent the 1:1 slope. ACP, Atlantic Coastal Plain; CCV, Central Valley, California; DCBAs, deep confined bedrock aquifers; GCP, Gulf Coastal Plain; HPA, High Plains (Ogallala) Aquifer; NAS, Nubian Aquifer System; NIAAs, northern India and adjacent areas; NCP, North China Plain; NWSAS, northwestern Sahara aquifer system; RPH, Rajasthan, Punjab, Haryana; WUABs, western U.S. alluvial basins; WVSs, western volcanic systems. R^2 denotes the coefficient of determination.

Mexico, Egypt, Kazakhstan, Spain, Italy, Turkey, South Africa, Morocco and Algeria. In some regions such as west United States and the Indo-Gangetic plains extensive larger and smaller diversion works are probably able to meet this outstanding demand by nonlocal water. In other less developed regions, it is common that farmers irrigate less than optimally because of persistent water scarcity or to minimize costs. Here, potential yields over current irrigated areas can still be improved if additional water resources were available for irrigation. Conversely, in China, Russia, Saudi Arabia, Argentina, Yemen and UAE, current irrigation practice is near optimal in terms of productivity. In these countries, current irrigated areas are almost fully exploited and their yields from irrigation can only be increased by improved water use efficiency (i.e., higher crop water productivity per unit irrigated area) or by expanding their irrigated areas. However in some of these countries where available blue water is almost fully used for irrigation, additional abstraction of nonrenewable groundwater will result in further depletion of groundwater resources.

[45] We reconstructed past trends of different water resources contributing to irrigated crops. We only provide global estimates here because of the rather strong assumption of a linear relationship between country-based groundwater abstraction and country net total water demand. Figure 7 shows that in irrigated areas the gross crop water demand more than doubled from 1217 to 2510 km^3 yr^{-1} over the period 1960–2000. For the year 1960, green water contributed globally 48% or 589 km^3 yr^{-1} to the gross crop water demand resulting in a gross irrigation water demand of 628 km^3 yr^{-1}. Blue water and nonrenewable groundwater supplied 73%, or 457 km^3 yr^{-1}, and 12%, or 75 km^3 yr^{-1}, of the gross irrigation water, respectively, leaving 15%, or 96 km^3 yr^{-1}, for nonlocal water resources. During the 1960–2000 period the global gross irrigation water demand more than doubled to 1338 km^3 yr^{-1} as a result of expansion of irrigated areas to support growing food demands. The amount of blue water contributing to the global gross irrigation water demand also increased to 844 km^3 yr^{-1} but its share decreased to 63% for the year 2000. However, the amount and share of nonrenewable groundwater rose to 234 km^3 yr^{-1} and close to 20%, respectively. These results suggest that available blue water resources have become extensively exploited for irrigation. Even though large numbers of reservoirs were constructed to supply water to irrigation, the increase in their storage capacities has been tapering off since the 1990s [*Chao et al.*, 2008]. Consequently, the contribution of nonrenewable groundwater abstraction to meet the gross irrigation water demand has been increasing rapidly, resulting in an increasing dependency on nonrenewable groundwater for irrigation in recent years.

4. Discussion

[46] Here, we first compare per major irrigated country our results with available statistics and previous estimates to explore the differences in crop and irrigation water

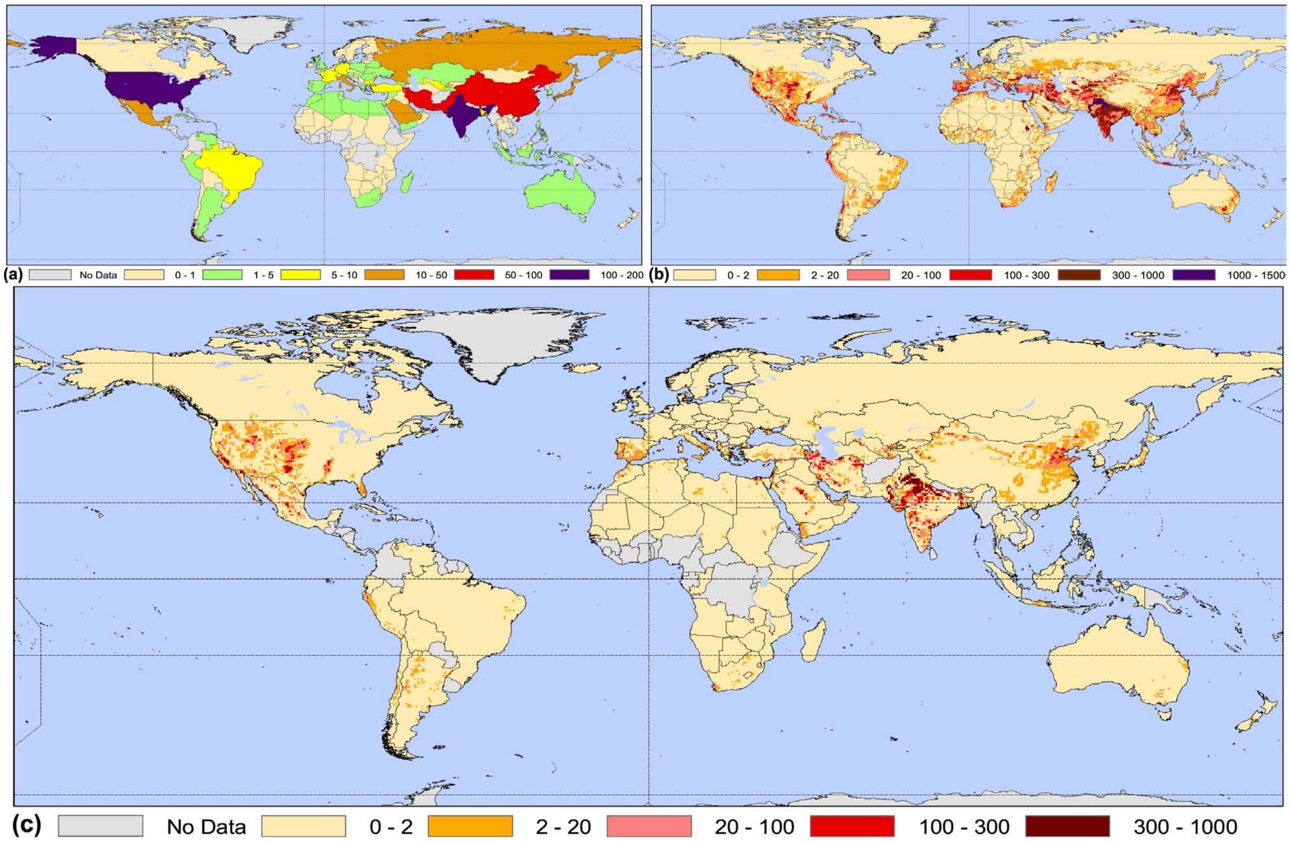

Figure 4. (a) Groundwater abstraction per country indexed to the year 2000 ($km^3\ yr^{-1}$), (b) estimated gross irrigation water demand for the year 2000 ($10^6\ m^3\ yr^{-1}$), and (c) gridded groundwater abstraction for irrigation for the year 2000 ($10^6\ m^3\ yr^{-1}$).

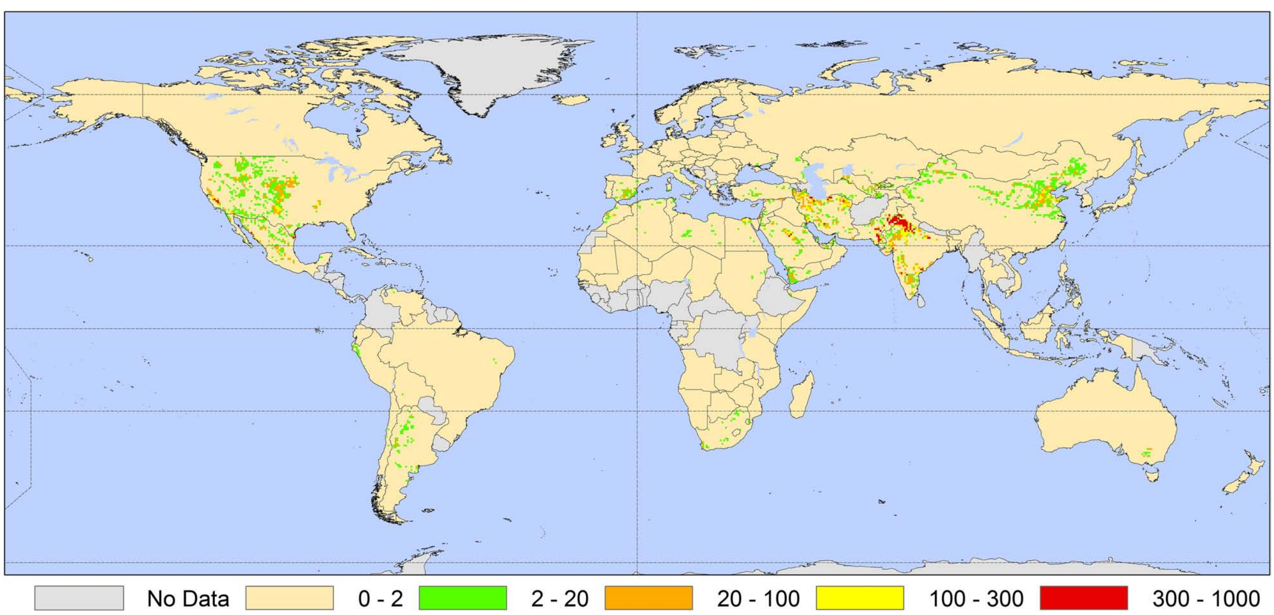

Figure 5. Nonrenewable groundwater abstraction for irrigation for the year 2000 ($10^6\ m^3\ yr^{-1}$).

Table 2. Contribution of Water Resources to Irrigated Crops (Gross Crop Water Demand in Irrigated Areas) in Major Groundwater Users for the Year 2000[a]

				Gross Irrigation Water Demand							
		Green Water Contribution		Total		Blue Water Contribution		Nonrenewable Groundwater Abstraction		Nonlocal Water Resources	
Country	Gross Crop Water Demand ($km^3\ yr^{-1}$)	$km^3\ yr^{-1}$	Percent	$km^3\ yr^{-1}$	Percent	$km^3\ yr^{-1}$	Percent	$km^3\ yr^{-1}$	Percent	$km^3\ yr^{-1}$	Percent
India	600	247	41	353	59 (100)	214	36 (61)	68	11 (19)	71	12 (20)
China	403	267	66	136	34 (100)	105	26 (77)	20	5 (15)	11	3 (8)
United States	204	77	38	127	62 (100)	77	38 (61)	30	14 (23)	20	10 (16)
Pakistan	183	37	20	146	80 (100)	81	44 (55)	35	19 (24)	30	17 (21)
Iran	59	9	15	50	85 (100)	19	32 (38)	20	34 (40)	11	19 (22)
Mexico	71	26	36	45	64 (100)	27	38 (60)	10	14 (22)	8	11 (18)
Saudi Arabia	14	1	7	13	93 (100)	3	22 (23)	10	71 (77)	0	0 (0)
Globe	2510	1172	47	1338	53 (100)	844	34 (63)	234	9 (18)	260	10 (19)

[a]Values in parentheses are the percentage of a water resource contributing to gross irrigation water demand.

demand. Next, we discuss limitations and uncertainties inherent to this study.

4.1. Comparisons With Previous Estimates

[47] We compared the estimated crop and irrigation water demand with reported and estimated values taken from the FAO and previous studies in Table 3. *Siebert and Döll* [2008] and *Liu and Yang* [2010] assumed that the contribution of green and blue water is sufficient to meet gross crop water demand and estimated blue water demand from this. *Rost et al.* [2008] quantified the amount of gross and net irrigation water demand (see equations (4) and (2), respectively) with and without the potential contributions of nonrenewable and nonlocal blue water resources to meet these demands (IPOT/ILIM; see Table 3). *Wisser et al.* [2008], on the other hand, assessed uncertainties of computing gross irrigation water demand by using two different data sets of irrigated areas based on the FAO (GMIA [*Siebert et al.*, 2005, 2007] and the IWMI (GIAM) [*Thenkabail et al.*, 2006]) with two different climate inputs of the National Centers for Environmental Prediction (NCEP) (NCEP/NCAR [*Kalnay et al.*, 1996] and the CRU (CRU TS 2.1) [*Mitchell and Jones*, 2005]).

[48] Our estimates of gross crop water demand for irrigated areas per country agree reasonably well with those of the other studies. For major irrigated countries such as India, China, and United States, we estimated gross crop water demand to be 600, 403, and 204 $km^3\ yr^{-1}$, respectively, while the other studies report 313–462, 404–492, and 218–265 $km^3\ yr^{-1}$. The variation is likely caused by differences in irrigated areas since we used FAOSTAT statistics to correct irrigated areas per country from the MIRCA2000 data set, while *Siebert and Döll* [2008] and *Liu and Yang* [2010] used the MIRCA2000 data set and that of *Siebert et al.* [2007], respectively. Differences in prescribed reference evapotranspiration which is used to compute crop water demand between this study and the other studies should also explain the variation. Our estimates of irrigation water demand are close to the reported values of FAO and those of *Siebert and Döll* [2008] for most of the countries. Range is large for irrigation water demand estimates from the other studies. This is because *Wisser et al.* [2008] account for uncertainties caused by different irrigated area estimates combined with different climate inputs. For India, the use of the IWMI irrigated areas doubles the estimated gross irrigation water demand compared to the estimate based on the FAO irrigated areas, while the climate input of the NCEP results in lower values compared to that of the CRU. The same trend applies for China, but not for the United States and Egypt; here both FAO and IWMI report similar areas yet the gross irrigation water demand decreases when the NCEP climate data are used. Globally, gross irrigation water demand is larger by 30% when using IWMI irrigated areas instead of the FAO data, while it decreases by the same magnitude when NCEP instead of CRU climate data are used [*Wisser et al.*, 2008].

[49] Our blue water contribution to irrigation is generally lower than reported by other studies, because we partitioned blue water contribution into renewable and nonrenewable resources, while blue water contribution of the previous studies include both terms. If we combine both terms, our blue water contribution becomes close to existing estimates. *Rost et al.* [2008] implicitly quantified amounts of nonlocal and nonrenewable water resources used for irrigation (i.e., IPOT and ILIM). For India and China, their values are larger than our estimates of nonrenewable groundwater and nonlocal water resources whereas they are comparable to our values for the United States, Pakistan and Egypt. Our green water contribution to irrigated crops per country is close to those of *Siebert and Döll* [2008] and *Liu and Yang* [2010] since we used the same CRU climate data set as forcing.

4.2. Limitations and Uncertainties

[50] Limitations of this study largely result from uncertainties caused by input data and modeling assumptions. For example, as in previous studies [e.g., *Döll and Siebert*, 2002; *Rost et al.*, 2008; *Wisser et al.*, 2008; *Siebert and Döll*, 2010; *Hanasaki et al.*, 2010], growth of irrigated crops to compute crop water demand with crop calendar is simulated in a rather simple manner which only approximates actual water use conditions. Simulating optimal irrigation likely causes overestimation of crop water demand

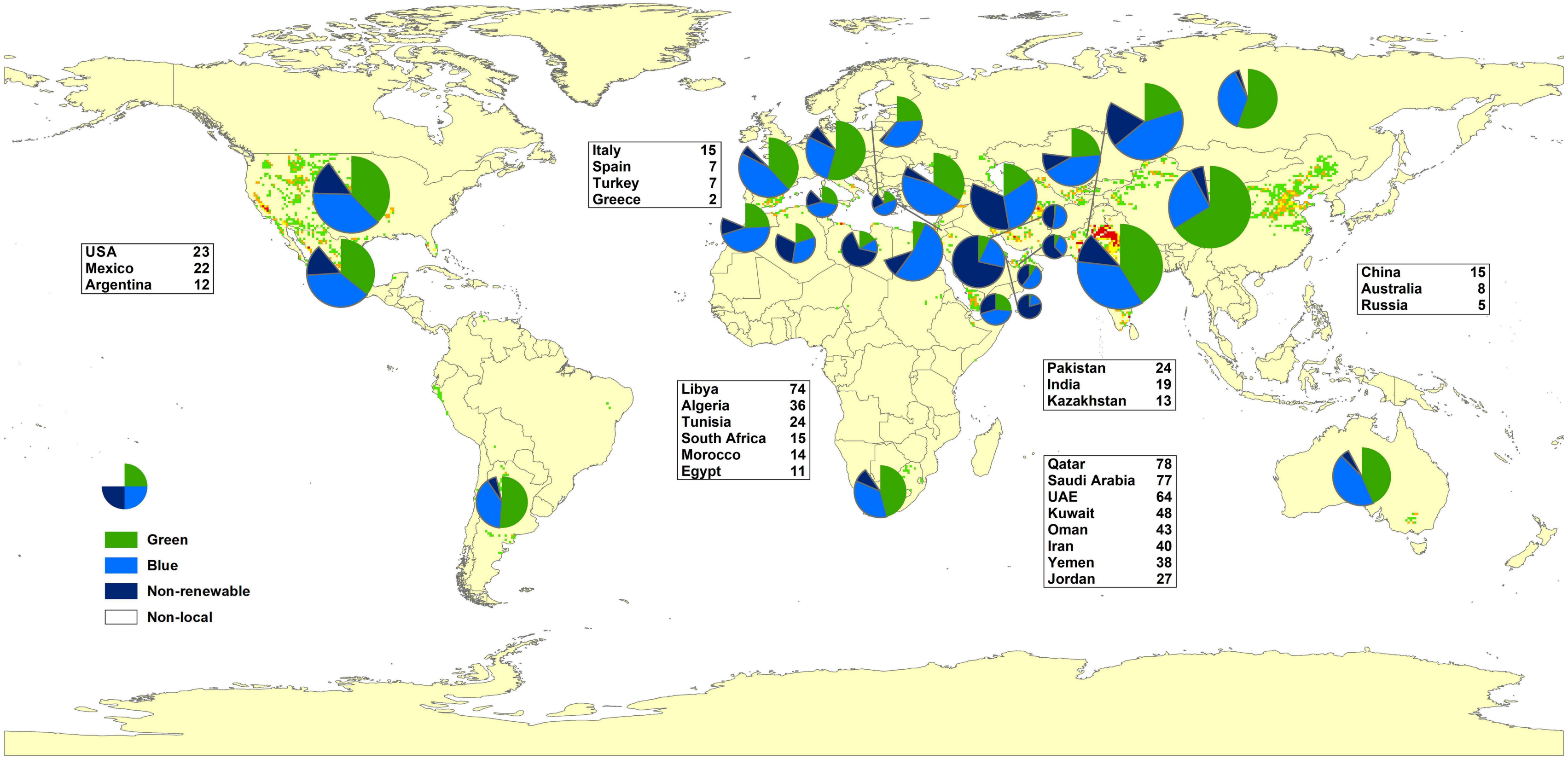

Figure 6. Current contribution per water resource to water used for irrigated crops (gross crop water demand in irrigated areas) for major groundwater users. Background shows a map of nonrenewable groundwater abstraction for irrigation. Labels indicate percentages of nonrenewable groundwater abstraction contributing to gross irrigation water demand (%). Sizes of pie charts are relative to amounts of gross crop water demand in irrigated areas among the countries shown.

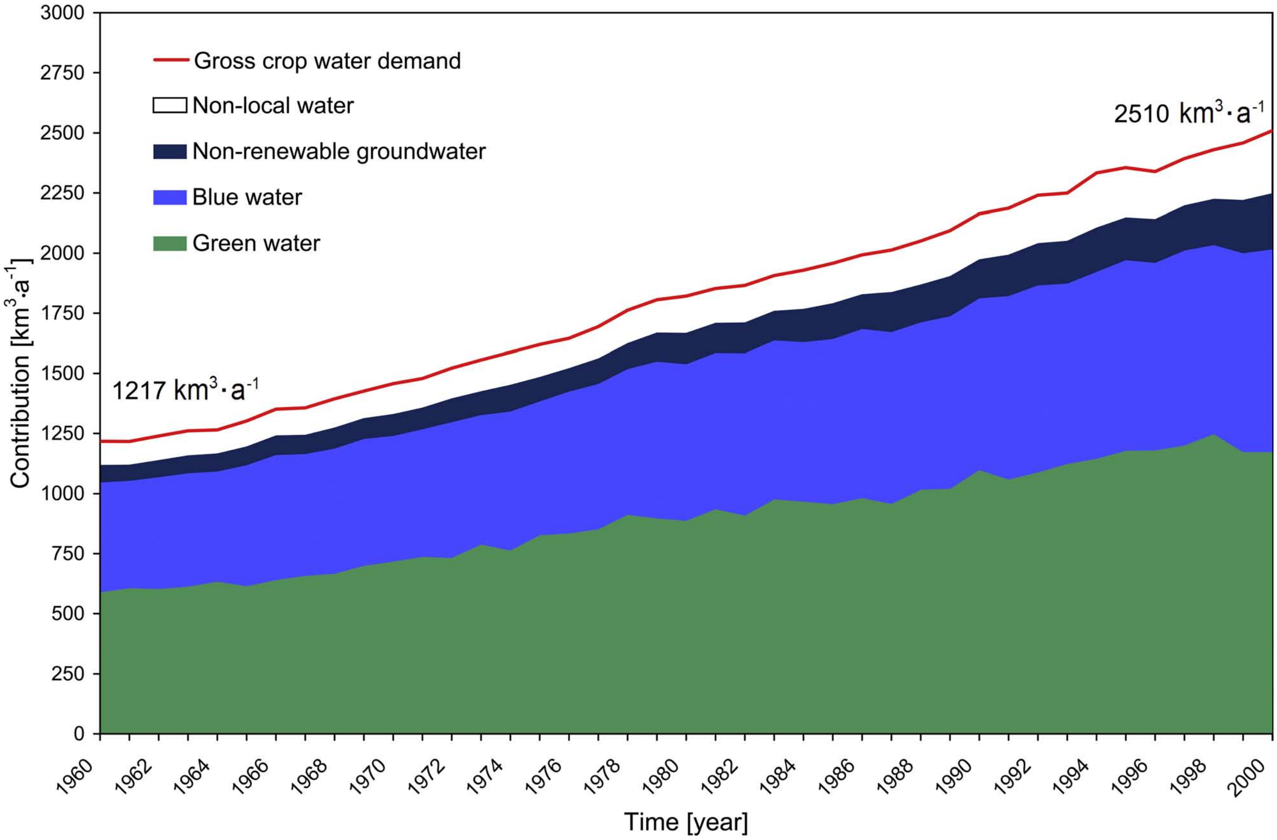

Figure 7. Past trends in the contribution per water resource to the global gross crop water demand. Green, green water; Blue, blue water; dark blue, nonrenewable groundwater. The white area between gross crop water demand and the three available water resources denotes the estimated contribution of nonlocal water resources (all in km^3 yr^{-1}).

in regions where persistent water scarcity leads farmers to irrigate less than the optimal conditions [*Döll and Siebert*, 2002] such as India, Pakistan, Iran and Egypt.

[51] The amount of soil moisture (i.e., green water) and surface freshwater (i.e., blue water) available to irrigated crops were simulated by PCR-GLOBWB. Extensive validations of PCR-GLOBWB were performed by *Van Beek et al.* [2011] by comparing the simulated river discharge to observations [*Global Runoff Data Centre* (*GRDC*), 2008] and the estimated actual evapotranspiration to that of the ERA-40 reanalysis as proxy for observed rates [*Kållberg et al.*, 2005]. Comparisons with over 3600 GRDC stations show that the coefficient of determination (R^2) is high ($\approx$0.9) for most of the stations but the coefficient of determination decreases when the mean minimum and maximum monthly discharge are considered instead of the mean discharge. Interannual variability is mostly well reproduced in major rivers except the Niger ($R^2 = 0.54$), Orange ($R^2 = 0.54$), Murray ($R^2 = 0.60$), Indus ($R^2 = 0.62$), Zambezi ($R^2 = 0.75$) and Nile ($R^2 = 0.87$) where the simulated river discharge is often also overestimated.

[52] Although strictly speaking not observational data, the ERA-40 reanalysis set can be seen as a proxy to actual evapotranspiration measurements because of the assimilation of atmospheric observations [*Kållberg et al.*, 2005]. Comparisons between our simulated actual evapotranspiration and that of the ERA-40 show that for the nonirrigated areas both data sets are quite similar and that differences can be largely explained by differences in rainfall estimates between ERA40 and CRU [*Van Beek et al.*, 2011]. However, for most of the major irrigated areas the simulated actual evapotranspiration of PCR-GLOBWB is generally smaller than that of the ERA-40 reanalysis. While seasonal courses are well reproduced during the wet season, the deviation widens during the dry season in heavily irrigated regions such as the Great Plains, Spain and Pakistan. The latter comes from the fact that, unlike evaporation from PCR-GLOBWB, ERA-40 evaporation is a reanalysis product. Because irrigation is not explicitly modeled in the ECMWF land surface model, screen temperatures will generally be overestimated over these areas because of an underestimation of the latent heat flux. Consequently, during the analysis steps, additional moisture is added to the soil moisture reservoirs in order to increase the subsequent latent heat fluxes and keep temperature as calculated by the numerical weather prediction model close to the observations. This "implicit irrigation scheme" resulting from data assimilation thus explains the higher evaporation rates of ERA40 during the dry irrigation season (see the work by *Van Beek et al.* [2011] and results therein). *Van Beek et al.* [2011] also showed that

Table 3. Comparisons With Previous Studies of Water Used for Irrigated Crops per Water Resource in Major Irrigated Countries Around the Year 2000[a]

	FAO	*Rost et al.* [2008][c]		*Wisser et al.* [2008]	*Siebert and Döll* [2008]			*Liu and Yang* [2010]			This Study				
Country	Blue[b]	Gross Blue	Net Blue	Gross Blue[c]	Crop	Green	Blue	Crop	Green	Blue	Crop	Green	Blue	NRGW	NLWR
India	303	710–715 (IPOT), 181–203 (ILIM)	385–387 (IPOT), 100–114 (ILIM)	FAO 390–590 (NCEP), 800–910 (CRU); IWMI 1100–1400 (NCEP), 1600–1800 (CRU)	462	175	287	313	171	142	600	247	214	68	71
China	154	404–409 (IPOT), 253–267 (ILIM)	203–206 (IPOT), 128–135 (ILIM)	FAO 220–480 (NCEP), 540–690 (CRU); IWMI 270–600 (NCEP) 690–850 (CRU)	404	257	147	492	279	213	403	267	105	20	11
United States		167–171 (IPOT), 92–97 (ILIM)	104–105 (IPOT), 54–58 (ILIM)	FAO 87–150 (NCEP), 130–140 (CRU); IWMI 66–130 (NCEP), 110–140 (CRU)	218	79	139	265	127	138	204	77	77	30	20
Pakistan	72	117–120 (IPOT), 35–57 (ILIM)	54–55 (IPOT), 18–29 (ILIM)		136	19	117	79	23	56	183	37	81	35	30
Iran	21				52	11	41	39	8	31	59	9	19	20	11
Mexico	19				51	24	27	32	17	15	71	26	27	10	8
Egypt	28	29–30 (IPOT), 14 (ILIM)	17 (IPOT), 7 (ILIM)	FAO 31–36 (NCEP), 36–41 (CRU); IWMI 15–18 (NCEP), 18–20 (CRU)	48	1	47	31	2	29	30	2	16	3	9
Saudi Arabia	7				13	1	12	6	2	4	14	1	3	10	0
Globe	824	2534–2566 (IPOT), 1161–1249 (ILIM)	1353–1375 (IPOT), 636–684 (ILIM)	FAO 2000–2400 (NCEP), 3000–3400 (CRU); IWMI 2500–3000 (NCEP) 3700–4100 (CRU)	2100	919	1181	1870	943	927	2510	1172	844	234	260

[a]Values are in $km^3\ yr^{-1}$. Crop, gross crop water demand; Green, green water contribution; Blue, Blue water contribution; NRGW, nonrenewable groundwater contribution; NLWR, contribution of nonlocal water resources; FAO, Food and Agricultural Organization; IPOT, Potential Irrigation; ILIM, Limited Irrigation; IWMI, International Water Management Institute; NCEP, National Centers for Environmental Prediction; CRU, Climate Research Unit.

[b]The FAO estimates are primarily based on 90 countries taken from the FAO AQUASTAT database (http://www.fao.org/nr/water/aquastat/water_use_agr/index.stm).

[c]The ranges show the minimum and maximum values during the simulation period of 1971–2000 [*Rost et al.*, 2008] and 1963–2002 [*Wisser et al.*, 2008].

the difference in dry season evaporation between ERA-40 and PCR-GLOBWB could largely be explained by the calculated irrigation water demand as also used in this paper.

[53] Uncertainties in the estimated groundwater abstraction also affect our results. Because of a lack of observations, the country data does not include nonreported groundwater abstractions, which might be prevalent over major irrigated regions such as northwest India and northeast Pakistan. For example, *Foster and Loucks* [2006] suggests the amount of groundwater abstraction in India to be around 240 km^3 yr^{-1} while we used 190 km^3 yr^{-1}. We identified main locations (i.e., grid cells) where groundwater is abstracted by using surface freshwater deficits over total water demand as a proxy. Validation result shows that groundwater abstraction rates were well reproduced by our downscaling approach as compared to reported values per county taken from the USGS (see section 3.1). Our approach thus improves upon the earlier estimate of nonrenewable groundwater abstraction of *Wada et al.* [2010] who used simply total water demand as a proxy.

[54] We quantified the residual between the simulated gross irrigation water demand and the available blue water resources and nonrenewable groundwater abstraction for irrigation as the estimate of the contribution of nonlocal water resources. This residue was particularly large in India, Pakistan, the United States, Iran, and Mexico. Although actual nonlocal sources such as water diversions, e.g., the Central Valley Project in the United States, irrigation canals in the Yamuna River, a major tributary of Indus, [*Sharma and Kansal*, 2010] and desalinated water use (globally 5 km^3 yr^{-1} in the year 2000), account for part of these nonlocal water resources, a considerable part of the residual water may be attributed to the uncertainties described above. It is unlikely that nonlocal water resources are sufficient to fill all the shortage. For example, if we use the amount of groundwater abstraction suggested by *Foster and Loucks* [2006] for India, our estimate of nonrenewable groundwater abstraction for irrigation increases by around 50% while the amount of nonlocal water resources decreases by the same magnitude. And if we overestimated the crop water demand based on optimal crop growth in India, a discrepancy to actual crop water use further reduces the amount of nonlocal water resources. The same conditions also apply to Pakistan and Iran where persistent water scarcity is prevalent.

[55] Since our global model does not include additional capture and surface water diversions (e.g., aqueducts), overestimation of nonrenewable groundwater abstraction occurs in some regions notably in north India, western U.S. alluvial basins, and Southern California (Los Angeles and San Diego area). However, it does not demonstrate the inadequacy of estimating depletion from the water budget but shows that the attribution of country total abstraction rates to grid-based rates using local surface freshwater deficit as a proxy has its limitations. This is a general limitation of all global modeling efforts: when viewed at individual cell scales, disparities are likely to occur, while the regional variation is adequately captured. Even though our method for computing large-scale nonrenewable groundwater abstraction has its limitations and uncertainties to be able to provide estimates across the entire globe, it yields adequate results when compared to the independent estimates (see Figure 3).

5. Summary and Conclusions

[56] This study provides a global overview of the amount of nonrenewable groundwater abstraction that contributes to gross irrigation water demand. Apart from estimates of green and blue water contribution to water supplied to irrigated crops by previous studies [e.g., *Falkenmark et al.*, 1997; *Jackson et al.*, 2001; *Döll and Siebert*, 2002; *Kundzewicz et al.*, 2007; *Rost et al.*, 2008; *Wisser et al.*, 2008; *Siebert and Döll*, 2010; *Hanasaki et al.*, 2010; *Liu and Yang*, 2010], we explicitly quantified the amount of nonrenewable groundwater abstraction for irrigation by confronting the sum of the simulated natural groundwater recharge and additional recharge from irrigation with the gridded groundwater abstraction for irrigation. Thus, our blue water denotes exclusively renewable surface freshwater and groundwater which is closer to its definition. Optimal growth of irrigated crops and available green water and blue water to meet gross crop water demand were simulated by applying a state-of-the-art global hydrological model PCR-GLOBWB. The resulting shortage between gross irrigation water demand and available blue water and nonrenewable groundwater abstraction was calculated as an estimate of nonlocal water resources.

[57] The results of this study show that nonrenewable groundwater abstraction globally contributes nearly 20%, or 234 km^3 yr^{-1}, to the gross irrigation water demand for the year 2000 and has more than tripled in size since the year 1960. Country assessments reveal that nonrenewable or nonsustainable groundwater supplies large shares of current irrigation water particularly for semiarid regions where surface freshwater and rainfall are very scarce: Pakistan, Iran, Saudi Arabia, Libya, UAE and Qatar. Much of current irrigation in these regions is sustained by nonsustainable groundwater.

[58] The reconstructed development from 1960 to 2000 shows an increased dependency of irrigation on nonsustainable groundwater with time. Thus, irrigation is more and more sustained by an unsustainable water source. Severe competition for scarce surface freshwater resources for irrigation also worsens the condition of depleting groundwater resources. We argue that the unsustainability of groundwater use for irrigation is an important issue not only for the countries with intensive groundwater use, but also for the world at large since international trade directly links food production in one country to consumption in another. Rising population and their food demands are likely to increase the amount of nonrenewable groundwater abstraction for irrigation, particularly in emerging countries such as India, Pakistan, China, Iran and Mexico. This will result in falling groundwater levels which may eventually become unreachable for local farmers with limited technology. Groundwater resources have supported their livelihoods to generate their food and income for decades. Limits to global and regional groundwater consumption cast large uncertainties on their livelihoods, threatening regional and global food security. Groundwater depletion is a long outstanding issue, and various efforts have been made to explore solutions [*Moench et al.*, 2003], yet it is far from resolved. This study gives further evidence to scale of the issue and its growing trend. It is urging to invest further political, institutional and economic efforts to limit the overdraft, yet important to

find adaptive responses that do not reduce current food productivity.

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