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Key Points:
- We estimate the shadow price of irrigation water for the most important groundwater-depleting countries and five crops
- Large differences in shadow prices within countries indicate inefficient use of water resources, including nonrenewable groundwater
- Changes in water allocation could lead to large reductions in nonrenewable groundwater consumption

Supporting Information:
- Supporting Information S1
- Supporting Information S2
- Data Set S1
- Data Set S2
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- Data Set S4
- Data Set S5
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The Shadow Price of Irrigation Water in Major Groundwater-Depleting Countries

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Abstract In many semiarid regions with irrigation, the depletion rate of groundwater resources has increased substantially during the last decades. A possible reason for this is that the price that users pay for their water does not reflect its scarcity and value. An alternative way to assess the perceived value of water is calculating its shadow price, which is defined here as the marginal value produced, and relates to the efficiency gain from current reallocation. Here we determine the shadow price of water used for irrigation for the most important groundwater-depleting countries and for four staple crops and one cash crop. To quantify the shadow price, the relation between the output and the water input is represented using production functions. We use globally available panel data on country-specific crop yields and prices together with crop-specific water consumption, calculated with the global hydrological model PCR-GLOBWB, to parameterize the production function by country and crop with econometric analyses. Our results show that the variation of shadow prices for staple crops within several countries is high, indicating economically inefficient use of water resources, including nonrenewable groundwater. We also analyze the effects of reallocating irrigation water between crops, showing that changes in water allocation could lead to either an increase in the economic efficiency of water use or large reductions in irrigation water consumption. Our study thus provides a hydroeconomic basis to stimulate sustainable use of finite groundwater resources globally.

1. Introduction

Population growth and changing consumption patterns have greatly increased the demand for food (Godfray et al., 2010), and this trend is expected to persist into the 21st century (Valin et al., 2014). The demands for calories and proteins has been projected to double by 2050, resulting in extensive land use change between 0.2 and 1 billion ha depending on technological change (Tilman et al., 2011). As land use change is also associated with the expansion of irrigated land, surface water and groundwater use has been rising drastically (Wada et al., 2011) and, exacerbated by climate change, will increase further in the future (Haddeland et al., 2013; Wada et al., 2013). The expansion of irrigated agriculture into areas with limited precipitation and surface water during the growing season has increased the use of nonrenewable groundwater, that is, groundwater withdrawn that is not expected to be recharged on human time scales (>100 years; Gleeson et al., 2012). As a result, the depletion rate of groundwater resources has increased during the last decades (De Graaf et al., 2017; Konikow, 2011; Richey et al., 2015; Wada et al., 2010; Wada, van Beek, Sperna Weiland, et al., 2012) and is likely to persist in the decades to come (Wada, van Beek, & Bierkens, 2012; Wada, van Beek, Sperna Weiland, et al., 2012).

Agriculture is by far the largest user (i.e., 80%) of fresh water globally (Wada et al., 2011), but most farmers barely pay the actual costs associated with their (ground)water use. Often, policy with respect to groundwater use is either insufficient or lacking. In many countries, groundwater is freely available for land owners or users who purchase a water pump installation (Famiglietti, 2014), the supply of groundwater is not measured, and farmers may not consider the needs of future generations in their production decisions.

Under a situation of water shortage, water pricing is suggested as one of the economic incentives to limit the excessive overuse of water resources and to stimulate the application of water for higher-value uses (e.g., Dinar et al., 2015; Medellín-Azuara et al., 2012; Rinaudo et al., 2012). However, the economic scarcity of water is rarely reflected by a functioning market with competitive water pricing due to various disturbances associated with insufficient property rights, externalities, governmental price control, monopoly of water supply, and so forth (Jia et al., 2016). As a consequence, the price that users pay for their water does not reflect its scarcity. For example, farmers in Pakistan and parts of India receive energy subsidies that reduce the withdrawal costs of groundwater to almost negligible.

The actual price paid for groundwater usually consists of costs of groundwater extraction and transportation only (Ziolkowska, 2015). Not included in these are the following (Rogers et al., 1998): opportunity costs resulting from depriving other more profitable types of water use (now and in the future); environmental externalities, such as the costs of ecosystem deterioration due to lowering groundwater tables and diminished low flows; and economic externalities, for instance, related to declining water tables or heads resulting in stranded production wells (Perrone & Jasechko, 2017) or increased extraction costs for future users (Foster et al., 2015).

The fact that groundwater's price does not reflect its scarcity may result in inefficient groundwater allocation and depletion of aquifers (Organisation for Economic Cooperation and Development, 2015; Ziolkowska, 2015). The proposed underlying economic mechanism behind depletion is as follows: The farmer is assumed to be a price taker (i.e., cannot affect prices of inputs and outputs) and a profit maximizer. Therefore, production decisions are based on maximizing profit; that is, the farmer will continue production until the marginal costs are equal to the marginal revenue. Given the marginal cost of the water input, which is the price the farmer pays for an additional unit of water, the farmer will add water until he or she reaches maximum profit. When the price of groundwater is lower than the actual scarcity value, the farmer faces lower marginal costs and he or she will thus use more groundwater until he or she reaches maximum profit. This process stimulates depletion.

In absence of a water market or actual water pricing, the value of water for irrigation is often determined using a shadow price (Liu et al., 2009; Mesa-Jurado et al., 2010; Young & Loomis, 2014; Ziolkowska, 2015). The shadow price of water has many definitions in the literature (e.g., He et al., 2007); the shadow price can be computed either based upon the farmer's behavior or based upon the value of alternative use (e.g., different user or different time). We will discuss four definitions: (1) First, it may be defined in the context of optimizing groundwater withdrawal over time when groundwater is being depleted as a result of temporarily extracting more than recharge (Burt, 1964). The goal is to find the optimal or efficient withdrawal rate over time that maximizes the net present value of the groundwater used. It can be shown that this intertemporal efficiency is achieved if, at every moment in time, the net return (revenue minus costs) from a marginal unit of extracted groundwater is equal to the marginal value of groundwater that remains in the ground (Burt, 1964, 1967; Gisser & Sánchez, 1980; Negri, 1989). This marginal value is called the shadow price, and it is generally calculated as co-state variable when solving the intertemporal optimization problem with the water balance of the aquifer as a constraint (Negri, 1989). (2) An even more extensive definition of shadow price refers to the price that would need to be paid by farmers to veritably account for the actual value of water as a scarce resource including all costs (including intertemporal efficiency, opportunity costs, and environmental and economic externalities), which is often unknown (Elnaboulsi, 2001; Kaiser & Roumasset, 2002; Tsur & Graham-Tomasi, 1991; Young & Loomis, 2014). (3) Another definition follows from residual valuation (Colby, 1989), which is based on the assumption that all inputs (excluding water) are applied according to their (market) price. Here the shadow price of water for irrigation can be calculated as the ratio between the net returns of crop production and the total amount of water used for irrigating (Berbel et al., 2011; Hellegers & Davidson, 2010). (4) Finally, if farmers do not take intertemporal efficiency into account (they ignore future groundwater use), the shadow price can also be referred to as the current marginal value of water (He et al., 2007; Wang & Lall, 2002; Young & Loomis, 2014). This reflects the value that water has to the farmer, that is, the maximum price the farmer is willing to pay for the last cubic meter of irrigation water consumed. This is the definition used in this paper.

The following definition of shadow price is therefore used: The shadow price of water reflects the value of crops that can be produced by the marginal unit water consumed, given the quantity of the other inputs (e.g., labor and fertilizer). Applied to irrigation, this means the revenue (production times market price) produced with the last cubic-meter water consumed. Producers will only employ an input (ceteris paribus) up to the point where its price is just equal to the additional value derived by employing an additional unit of input (Williams et al., 2017). By this definition, a low shadow price entails a low revenue per cubic-meter water consumed and, in case of countries or regions with a considerable fraction of irrigation water coming from nonrenewable groundwater, reveals wasteful use of a nonrenewable resource. A low shadow price thus indicates that the application of nonrenewable groundwater can generate higher revenue by using it for crops with a higher shadow price.

As follows from the short review on the various definitions of shadow price used, the definition used in this paper does neither consider intertemporal efficiency nor include opportunity use. Thus, rather than focusing on the more general issue of nonrenewable groundwater use now and in the future, our paper has the narrower focus on the efficient allocation of irrigation water, including nonrenewable groundwater, currently abstracted. However, this strategy is not that uncommon if many farmers are pumping water from the same aquifer. Due to pumping externalities (Negri, 1989), the individual farmer cannot expect to have more water in storage next year if he or she pumps less. Thus, instead of maximizing the present value across time, farmers tend to maximize current net return, which is a free competition strategy that results in a shadow price as used in this paper. Gisser and Sánchez (1980) show that in certain cases, competition results in depletion rates and shadow prices that are similar to those obtained under optimal intertemporal control, a result that has been found for a number subsequent studies (Koundouri, 2004). Even though this so-called Gisser and Sánchez effect partly motivates the approach taken in this paper, we cannot claim that the Gisser and Sánchez effect is ubiquitous. Especially in heavily stressed aquifers, where the costs of extraction become very high (Koundouri, 2000) or externalities are considerable (Esteban & Albiac, 2011; Foster et al., 2015), intertemporal inefficiencies are found to be very important.

In this paper, we determine the shadow price of irrigation water (including nonrenewable groundwater) for the most important groundwater-depleting countries and for four staple crops (wheat, maize, rice, and potato) and one cash crop (citrus). These staple crops represent the top four crops in terms of global production (FAOSTAT, http://www.fao.org/faostat). To quantify the shadow price, that is, the marginal value of water, the relation between the output and the water input is represented using production functions. We use globally available panel data on country-specific crop yield and prices (Food and Agriculture Organization of the United Nations, 2016a, 2016b) together with groundwater and surface water consumption from a global hydrological model (Van Beek et al., 2011; Wada et al., 2014) to parameterize the production function by country and crop using econometric analyses. With "consumption" or "consumptive use" we refer to the water that is evaporated (by transpiration, interception, and soil evaporation) at the field during crop production. Preferably, we would have liked to determine the shadow price of nonrenewable groundwater only, instead of irrigation water. However, it cannot always be assumed that nonrenewable groundwater is the marginal water type allocated. For instance, in case surface water rights are scarce and expensive, groundwater (even nonrenewable groundwater) would most likely be used first. Moreover, as our study is at country scale, it is certainly possible that groundwater and surface water are used at the margin in different parts of a country. Hence, for lack of detailed information about the order of application of surface water and (nonrenewable) groundwater, we determine the shadow price of irrigation water as a whole. However, as we focus on the top groundwater-depleting countries in the world, a relatively low shadow price of irrigation water also indicates that nonrenewable groundwater is used inefficiently.

The comparison of shadow prices between crops within a country thus provides clues to where groundwater overuse can be reduced with minimal loss of revenue. Conversely, if reduction of nonrenewable groundwater consumption is not a target, a reallocation of nonrenewable groundwater can be sought that maximizes economic return, which would in turn provide funds for investments in water-saving technology or more efficient agriculture. Apart from optimal allocation, a shadow price would be useful information for water pricing (Dinar et al., 2015) and as an indication of the compensation paid in paying for ecosystem services schemes (Immerzeel et al., 2008; To et al., 2012). Finally, as it measures the efficiency of water use for specific crops, it may be used as to compute the value of the virtual water content of crops and products using water-footprinting tools (Mekonnen & Hoekstra, 2011).

Obviously, this is not the first study to estimate the shadow price of water, as testified by the review presented above. However, our study provides several advances. First, it is the first analysis of global context looking at the countries with largest groundwater use, which allows for the comparison of the efficiency of water use between countries. Second, by focusing on countries with considerable groundwater depletion, it specifically looks at nonrenewable groundwater, which is a water source that is increasingly being used globally under limited renewable water resources. Third, unlike most studies that take reported water withdrawal data as basis for their analysis, we assess the shadow price econometrically based on consumptive water use, that is, the actual water used (evaporated) under crop production.

2. Data and Methods

2.1. Data

We focus on 11 countries with largest groundwater depletion globally (in terms of volume) and have analyzed five crops for each country. These countries are China, Egypt, India, Iran, Italy, Mexico, Pakistan, South Africa, Spain, Turkey, and the United States. Even though it ranks higher in volume of groundwater depletion than some of the other countries analyzed, Saudi Arabia is excluded, because of the small areas of the crops considered, which caused a large unbalance in the estimation results. For each crop, we collected information on yield, total area, and prices retrieved from the FAO database (Food and Agriculture Organization of the United Nations, 2016a, 2016b) for the years 1971–2010 (prices are available for 1991–2010). We distinguish three sources of water: green water, blue water, and nonrenewable groundwater (Oki & Kanae, 2006). Green water is water that is taken from the soil by the plant that originates from rainfall. Rainfed agriculture thus relies completely on green water, although some rainfed agriculture is irrigated during severe droughts. Blue water is the renewable water that is additionally supplied by irrigation. It consists of surface water taken from a reservoir/storage, a river, or renewable groundwater. The final source of water is nonrenewable groundwater, which is water taken out of storage by persistent groundwater overuse that will not be recharged on the human time scale (>100 years; Wada et al., 2010; Gleeson et al., 2016). For each water source, we calculate the water consumption, that is, the water that is used by the cropping system through crop transpiration, interception evaporation, and soil evaporation.

The green water, blue water, and nonrenewable groundwater together make up all water that is actually used by irrigating crops. To calculate these quantities per crop and per country, we used the global hydrology and water resources model PCR-GLOBWB (Sutanudjaja et al., 2018; Van Beek et al., 2011; Wada et al., 2014). PCR-GLOBWB is a global hydrology and water resources model that runs at 5-arcmin resolution (~10×10 km at the equator) at a daily time step. For each grid cell and each time step, PCR-GLOBWB calculates soil moisture storage in two soil layers, as well as the water exchange between the upper soil layer and the atmosphere and the lower soil layer and the underlying groundwater reservoir. The exchange with the atmosphere consists of precipitation, evaporation from soils, open water, snow and soils, and plant transpiration. The model also simulates snow accumulation, snowmelt, and glacier melt. Subgrid variability of land use, soils, and topography is included. PCR-GLOBWB also includes hydrological parameterizations for runoff-infiltration partitioning, interflow, groundwater recharge, and groundwater discharge. Runoff generated by snow and glacier melt, surface runoff, interflow, and groundwater discharge is routed across the river network to the ocean or endorheic lakes and wetlands.

PCR-GLOBWB includes over 6,000 man-made reservoirs (Lehner et al., 2011) that are introduced consecutively in time based on their completion date. For each reservoir, a simple operation scheme is applied based on its main purpose. Human water use is fully integrated with the hydrological model such that at each time step, (1) the quantity of water demand is estimated for irrigation, livestock, industry, and households; (2) these demands are used to estimate actual withdrawal from groundwater and surface water (rivers, lakes, and reservoirs) dependent on availability of these resources and on maximum groundwater pumping capacity in place (following International Groundwater Resources Assessment Centre; https://www.un-igrac.org/); and (3) as a last step, consumptive water use (water consumption) and return flows are then calculated per sector. In PCR-GLOBWB, green water, blue water, and nonrenewable groundwater sources are used by crops in a sequence. First, green water is used, then blue water, (if available or in case of reservoirs upstream), and finally, if a water shortage still exists and groundwater is available, nonrenewable groundwater is used. We note, however, that in reality the order that these types of water are used may be different, depending on regional physiography and institutional context. In earlier studies, PCR-GLOBWB has been extensively validated against observed or reported data including runoff and river discharge (Van Beek et al., 2011), sectoral water use and groundwater pumping (Sutanudjaja et al., 2018; Wada et al., 2011), and total water storage (Sutanudjaja et al., 2018; Wada et al., 2014). We refer to these studies for further details.

PCR-GLOBWB was forced with the WFDEI (WATCH Forcing Data methodology applied to ERA-Interim reanalysis data) meteorological data set (Weedon et al., 2014) and run twice for the period 1991–2010. The first run was performed without human water use, simulating rainfed agriculture only. The actual evaporation (evaporation plus plant transpiration) was calculated per crop and per grid cell for the irrigated areas and summed up per crop per year for each of the 12 countries. This provided an estimate of green water consumption. The second run, which included human water use, resulted in blue water and nonrenewable groundwater consumption per crop and per cell over the irrigated areas, which was again summed per crop per year for the 12 countries considered. Also reported was the irrigated area of each crop as used in PCR-GLOBWB, which was obtained from MIRCA2000 (Portmann et al., 2010). Finally, as a measure of the intensity of other inputs (e.g., capital and variable inputs), we also obtained energy input per capita for each country from the World Bank data portal (https://data.worldbank.org) (see also Table S1 (supporting information)). The resulting set of panel data (crop yield, crop area, green water, blue water, nonrenewable groundwater, irrigation water [the sum of blue water and nonrenewable groundwater], and energy input), per year for the period 1971–2010 for 11 countries is subsequently used for estimating the shadow price per crop and per country. Table 1 provides the structure of the panel data. Table S2 (supporting information) provides the summary statistics of the panel data used.

2.2. Estimating Shadow Prices

The marginal product of irrigation water is determined by estimating a production function and taking the partial derivative with respect to irrigation water. The production function has to fulfil certain conditions (e.g., concavity; Chambers, 1988), which will be tested for in the econometric estimation.

The production function is applied to model the production of crops based on agricultural land, marketable inputs (e.g., seed, fertilizers, and energy), and water input (Frank, 2010):

$$Y = f(A, X, W, e), \tag{1}$$

where

- Y crop production (kg);
- A agricultural land (ha);
- X vector of n marketable inputs (seeds, fertilizer, energy, labor, and capital);
- W vector of water inputs (green water GW and irrigation water IW (sum of blue water and nonrenewable groundwater [m^3]);
- e stochastic disturbance.

We can only use these inputs for which we have quantitative (measured) information available, except water inputs, which are simulated by the model, and therefore, we use production data at the country level from official (FAO and World Bank) statistics (see section 2.1). The impact of all these variables on the yield is estimated econometrically. The estimated parameters will be used to compute the value of an extra cubic meter of available irrigation water (the shadow price). We prefer to analyze the different effects of green water (the amount of green water applied is not influenced by the farmer) and irrigation water applied by the farmer on the crop yield. Therefore, we include green water (*GW*) and irrigation water (*IW*) as a separate input in the production function. We assume that the plant first uses the available green water and only irrigation water is applied if necessary.

A specification is needed to estimate the production function. The most widely used form is the Cobb-Douglas production function. If we consider land, marketable inputs, and two types of water inputs (green water and irrigation water), the Cobb-Douglas production function is represented by the following equation:

$$Y = \beta_0 \cdot A^{\beta A} \cdot X^{\beta X} \cdot GW^{\beta GW} \cdot IW^{\beta IW} \cdot e, \tag{2}$$

where the model coefficients β_i are estimated from

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Table 1
Structure and Explanation of the Panel Data Set

Variable name	Year	Country	area	bgwat_ha	greenw_ha	yield	en_ha	price	bluew_ha	nonrgw_ha
Explanation	Year reported	Country code	Crop area	Consumptive use irrigation water (bluew_ha + nonrgw_ha)	Consumptive use green water	Yield	Energy use	Crop price	Consumptive use blue water	Consumptive use nonrenewable groundwater
Notation in equation			A	IW	GW	Y	E	p		
Unit	year	—	ha	$m^3 \cdot ha^{-1} \cdot year^{-1}$	$m^3 \cdot ha^{-1} \cdot year^{-1}$	$kg \cdot ha^{-1} \cdot year^{-1}$	kg of oil equivalent $ha^{-1} \cdot year^{-1}$	$US/t	$m^3 \cdot ha^{-1} \cdot year^{-1}$	$m^3 \cdot ha^{-1} \cdot year^{-1}$
Possible values	1971–2010	Integer	≥0	≥0	≥0	≥0	≥0	≥0	≥0	≥0
Note	Order of data: loop over years first and over countries second						Energy use per ha arable land (not allocated to crops)	Only available for 1991–2010		

FAOSTAT country code	Country name
41	China
59	Egypt
100	India
102	Iran
106	Italy
138	Mexico
165	Pakistan
202	South Africa
203	Spain
223	Turkey
231	United States

Note. The following file is available for each crop separately. All values are country averages or totals per crop. See the supporting information for FAO and World Bank data sources.

$$\ln Y = \ln \beta_0 + \beta_A \ln A + \beta_X \ln X + \beta_{GW} \ln GW + \beta_{IW} \ln IW + e. \tag{3}$$

The marginal product of irrigation water input is equal to the marginal product of nonrenewable groundwater, if nonrenewable groundwater is applied at the margin.

The partial derivative of the production function with respect to a certain water source, for example, *IW*, gives the marginal product of this water source:

$$MP_{IW} = \frac{\partial \ln Y}{\partial \ln IW} \cdot \frac{Y}{IW} = \beta_{IW} \frac{Y}{IW}. \tag{4}$$

Multiplied with the output price, it gives the shadow price of the water source:

$$P_{\text{shadow}} = p_{\text{output}} \cdot MP_{IW}. \tag{5}$$

As can be seen, the shadow price depends on the marginal productivity of water, the average water consumption per kilogram crop and the crop price (equations (4) and (5)). If farmers apply water economically, the marginal irrigation water cost (price per unit water) equals the shadow price. In case the irrigation water price is less than the unobserved true water price (including production costs, opportunity costs, and externalities), the shadow price will be lower. Hence, in situations where farmers pay a price for irrigation water that includes all costs, the shadow price should be higher than that in cases where farmers receive subsidized irrigation water (either subsidized water or energy input) such as in Pakistan and India. Also, crops that require a large water input per kilogram output are likely to have a smaller shadow price, for example, rice.

Besides the Cobb-Douglas specification, also the quadratic and translog production function can be estimated. Yaron (1967) and Kiani and Abbasi (2012) use a quadratic production function with only water as input:

$$Y = a\beta_0 + \beta_1 W + \beta_2 W^2. \tag{6}$$

In the Cobb-Douglas production function specification it is assumed that all inputs are substitutes and that the elasticity of substitution between inputs is constant. Christensen et al. (1973) proposed the translog function and demonstrated that it is able to provide a wider range of substitution of transformation patterns than those restricted by the constant elasticity of substitution, implied in the Cobb-Douglas function. A translog production function is represented by the following equation:

$$\begin{aligned} \ln Y = {} & \beta_0 + \beta_1 \ln A + \sum \beta_{2n} \ln X_n + \sum \beta_{3j} \ln W_j + \frac{1}{2}\beta_4 (\ln A)^2 + \frac{1}{2}\sum \beta_{5nn} (\ln X_n)^2 + \frac{1}{2}\sum \beta_{6jj} (\ln W_j)^2 \\ & + \Sigma\beta_{7n} \ln A \ln X_n + \Sigma\beta_{8j} \ln A \ln W_j + \Sigma\Sigma\beta_{9nj} \ln X_n \ln W_j + e, \end{aligned} \tag{7}$$

where W is the vector of j water inputs (1 = green water GW and 2 = irrigation water IW) and X is the vector of n marketable inputs (e.g., 1 = seeds, 2 = fertilizer, 3 = plant protection, 4 = labor, 5 = capital, and 6 = energy).

As can be seen, the Cobb-Douglas production function is a restricted form of a translog production function (Ku & Yoo, 2012). The marginal product of the water input per water source is equally derived by taking the partial derivative of crop production with respect to the water input per type, $j = 1$ (GW) and $j = 2$ (IW):

$$MP_{W_j} = \frac{\partial \ln Y}{\partial \ln W_j} \cdot \frac{Y}{W_j} = \left(\beta_{3j} + \beta_{6jj} \ln W_j + \beta_{8j} \ln A + \beta_{9nj} \ln X_n\right) \cdot \frac{Y}{W_j}. \tag{8}$$

Upon first analysis, the correlation coefficients between the water inputs turn out to be significant, which may lead to multicollinearity and biased estimators when the production functions are estimated. A possible explanation for the high correlation coefficients is a common trend, due to, for example, technological progress, in our data. Therefore, we add a time trend to our empirical model. We use an F test (Greene, 2002, p. 102) to assess which specification is more appropriate: a translog production or a Cobb-Douglas production function. Finally, input elasticities are calculated to see if the estimated production function fulfils the properties of a production function (i.e., diminishing marginal productivity; Chambers, 1988; Boisvert, 1982).

The data used to estimate the production functions consist of a panel of 11 countries (see Table 1). Panel data analysis allows for repeated observations over the same units during a number of periods (Verbeek, 2012), such that both a fixed-effects model and a random-effects model can be estimated. Our estimates are likely to suffer from omitted variable bias, since no data are available for the labor, capital, and variable inputs (except energy) for the entire period. Given these properties of our data, panel data estimation is most appropriate for estimation of the production functions. Advantages of panel data estimation are as follows: the possibility of modeling of time and unit-specific effects; the smaller potential omitted variable bias; the separation of within and between variation; the smaller effect of multicollinearity; and more efficient estimates (Baltagi, 2008; Verbeek, 2012).

To further explore the effects of unobserved variable bias, we also estimated alternative models where we removed explanatory variables and compared estimated parameters with the original model and tested for differences in model fit. Also, we additionally tested if including a time fixed-effect model (time step years) would further correct for unobserved variable bias by testing its improvement over a model not including these effects. Because multicollinearity between explanatory variables makes parameter estimates sensitive to minor changes in specification, multicollinearity could cause deviations in the parameter estimates as a result of omitted variables. To test whether our specification is susceptible for multicollinearity, the variance inflation factor was computed for all crops and all independent variables (Greene, 2002, p. 57).

Usually, total production is used as a dependent variable in production functions. However, as the yield (kg/ha) does not differ as largely between the countries as crop production, the yield is preferred as the dependent variable, which enables comparison between countries. Using yield as a dependent variable implies that the inputs must be transformed into per-hectare units and that the interpretation of the parameters of the production function is slightly different. Adding a time trend as a dependent variable to account for technological development influencing crop yield results in the following yield production function (subscript i indicates country and t indicates time; for brevity, we only include one type of water and one type of marketable input X):

$$\ln\left(\frac{Y_{it}}{A_{it}}\right) = \gamma_0 + \gamma_1 \ \ln A_{it} + \gamma_3 \ \ln\left(\frac{X_{it}}{A_{it}}\right) + \gamma_4 \ \ln\left(\frac{W_{it}}{A_{it}}\right) + \gamma_4 \ \ln^2 A_{it} + \gamma_5 \ \ln\left(\frac{X_{it}}{A_{it}}\right) \ln A_{it} \\ + \gamma_6 \ \ln\left(\frac{W_{it}}{A_{it}}\right) \ln A_{it} + \gamma_7 \ \ln^2\left(\frac{X_{it}}{A_{it}}\right) + \gamma_8 \ \ln^2\left(\frac{W_{it}}{A_{it}}\right) + \gamma_9 \ \ln\left(\frac{X_{it}}{A_{it}}\right) \ln\left(\frac{W_{it}}{A_{it}}\right) + \gamma_{10} \ \ln t_{it} + e_{it}. \tag{9}$$

The parameters γ_i can be derived from the β_i of equation (7) (Veninga, 2017).

2.3. Reallocating Irrigation Water

The estimated econometric model can be used to guide reallocation of irrigation water consumption from crops with a low shadow price to crops with a higher shadow price. Since our focus is on groundwater-depleting countries, this reallocation would be targeted on improving the efficiency of the use of nonrenewable groundwater. The principle is schematically explained in Figure 1. As an example, Figure 1a shows revenue functions for two crops, which are obtained by multiplying the production functions of these crops (see Figure 4 hereafter) with the current crop prices. In this case, the revenues for crop 2 are higher than those for crop 1 over the entire domain, and this also means that the shadow price of crop 2 is larger than that of crop 1 throughout. In terms of efficiency of resources, it is reasonable to reduce the use of irrigation water for crop 1 and allocate this to crop 2. This is shown in Figure 1a where part of the irrigation water used by crop 1 (ΔIW_1) is used for reallocation. The result is a reduction of revenue for crop 1 ($R_1(IW_1) - R_1(IW_1 - \Delta IW_1)$). In case irrigation water largely consists of nonrenewable groundwater and it was to be reduced by a “payment for ecosystem services scheme” (Immerzeel et al., 2008), this reduction of revenue would be the amount paid to the farmer. Figure 1a also shows the increase in revenue in case all this reduced irrigation water for crop 1 would be consumed by crop 2, the crop with the higher shadow price. The net gain in revenue from the reallocation would then be

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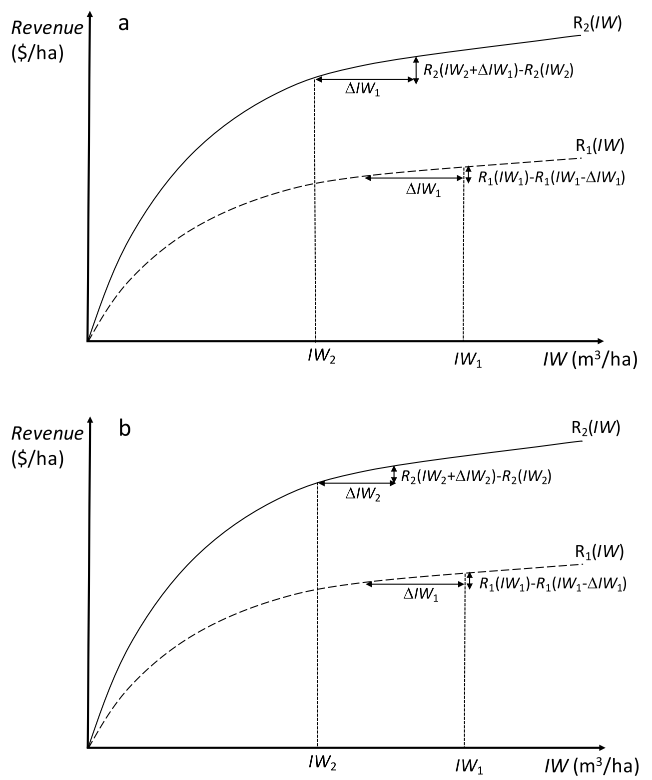

Figure 1. Reallocating irrigation water (*IW*) consumption in order to further efficient use or save nonrenewable groundwater (NRGW).
(a) Example of reallocating *IW* from a crop with low shadow price to one with a higher shadow price in order to increase revenue. Total revenue $R = R_1 + R_2$ increases, and total $IW = IW_1 + IW_2$ remains constant.
(b) Example of reallocating *IW* from a crop with low shadow price to one with a higher shadow price in order to decrease *IW* (and potentially NRGW) consumption. Total revenue $R = R_1 + R_2$ remains constant, and total $IW = IW_1 + IW_2$ decreases. $R_1(\,)$ and $R_2(\,)$ are revenue functions of crops 1 and 2, respectively; IW_1 and IW_2 are irrigation water consumption (including blue water and NRGW) of crops 1 and 2, respectively; and ΔIW_1 is reduction in *IW* consumption crop 1 and ΔIW_2 is increase in *IW* consumption crop 2.

$$\Delta R_{1\rightarrow 2} = R_2(IW_2 + \Delta IW1) - R_2(IW_2) + R_1(IW_1 - \Delta IW1) - R_1(IW_1). \quad (10)$$

Alternatively, the water reallocation can be aimed at reducing irrigation water (and potentially nonrenewable groundwater) consumption while maintaining the same level of revenue. This is shown in Figure 1b. Here not all the reduced irrigation water consumption by crop 1 (ΔIW_1) is used for crop 2, but a smaller amount ($\Delta IW_2 < \Delta IW_1$) to keep the total revenue constant. So we have the following (Figure 1b):

$$R_2(IW_2 + \Delta IW_2) - R_2(IW_2) = R_1(IW_1) - R_1(IW_1 - \Delta IW_1), \quad (11)$$

and the reduction of water consumption is equal to

$$\Delta IW_{1\rightarrow 2} = \Delta IW_1 - \Delta IW_2. \quad (12)$$

Although it may potentially save nonrenewable groundwater, reducing irrigation water consumption while keeping revenues constant is only (economically) efficient if the water saved is additionally allocated to other more profitable uses elsewhere or in the future.

To summarize the differences between Figures 1a and 1b, we have the following: In Figure 1a total revenue $R = R_1 + R_2$ increases and total irrigation water consumption $IW = IW_1 + IW_2$ remains constant, while in Figure 1b total revenue $R = R_1 + R_2$ remains constant and total $IW = IW_1 + IW_2$ decreases. Note that in the case described here, we portray two nonoverlapping curves, with the revenue for crop 2 larger than that of crop 1 for all values of *IW*; that is, the functions do not cross. This is the case if the elasticity related to irrigation water as input (γ_{IW}) in the production function of crop 2 is larger than that of crop 1 ($\gamma_{IW2} > \gamma_{IW1}$) and if at the same time the market price of crop 2 (p_2) is larger than that of crop 1 ($p_2 > p_1$). It also follows that in this case the shadow price of crop 2 is higher than that of crop 1 for all values of *IW*. This means that we can predict from the shadow price alone if a reallocation of *IW* from one crop to another will yield increased revenue or decreased water consumption. However, if $\gamma_{IW2} > \gamma_{IW1}$ and $p_2 < p_1$ (or vice versa) the curves will cross at some point. In this case, one has to evaluate equations (10) or (11)/12 to assess whether reallocating water from one crop to another will indeed lead to water saving or revenue increase. This shows that the shadow price is a measure of the marginal return and efficiency.

3. Results

3.1. Sources of Consumptive Water Use Per Country

Figure 2 shows the results of the simulations with PCR-GLOBWB, showing average consumptive water use by water type for crop production over the period 1971–2010. Countries like Iran, Saudi Arabia, and Pakistan stand out by the large proportion of agricultural water that comes from nonrenewable groundwater. This confirms earlier work by Wada, van Beek, and Bierkens (2012).

3.2. Estimated Parameters of the Production Function

Using panel data from 11 countries (Table 1 and supporting information Data), we estimated the parameters of production functions per country and per crop. We compared the translog model (equation (9)) with the Cobb-Douglas model and, using an *F* test on nested models, found the translog model explains the data significantly better than does the Cobb-Douglas model (supporting information Table S2). However, in the translog specification we found elasticities that are inconsistent with the production function theory (Chambers, 1988) (supporting information Table S3); that is, they should be smaller than 1 for

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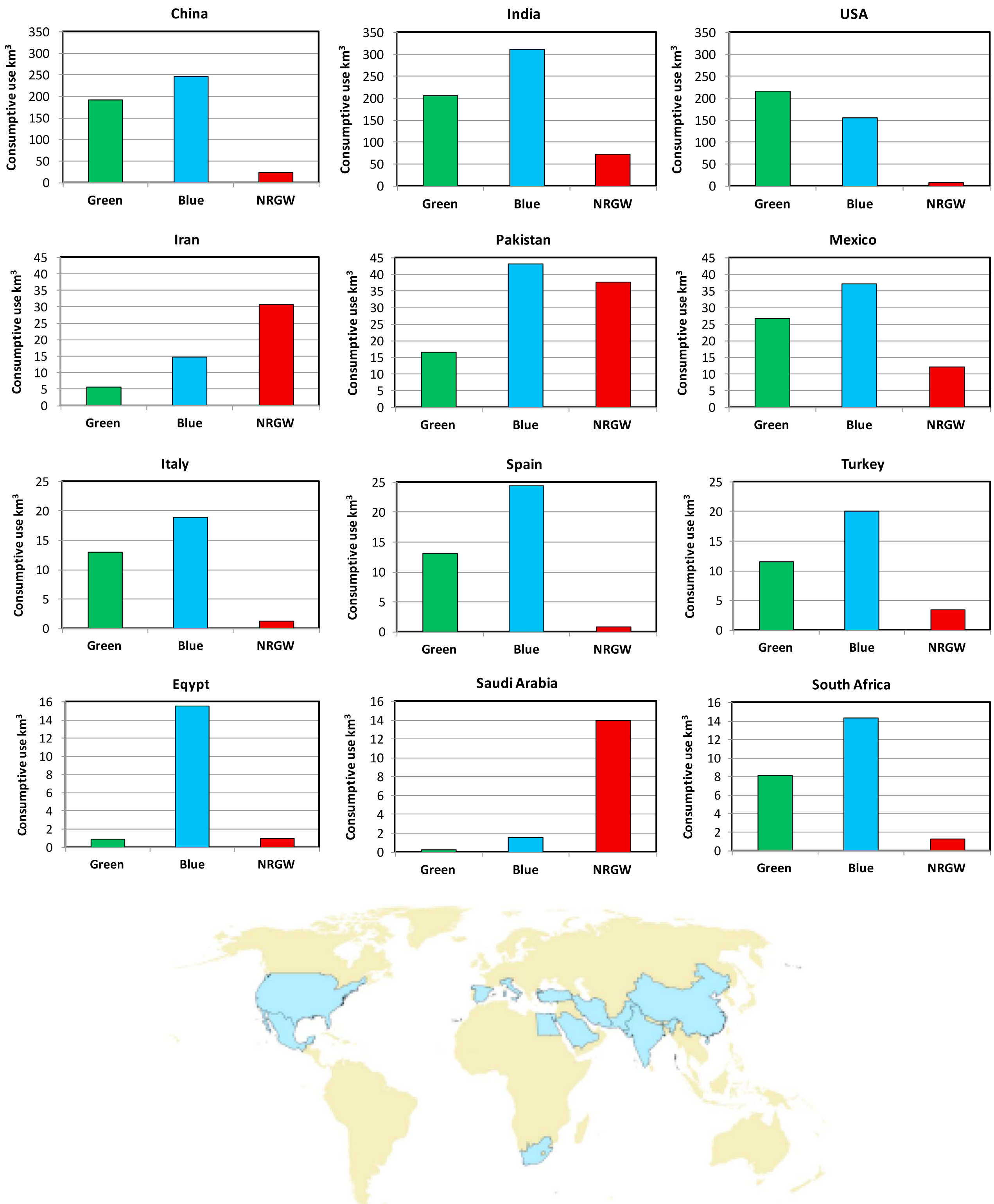

Figure 2. Consumptive water use for crop production by water type (green water, blue water, and nonrenewable groundwater [NRGW]; km^3/year) for 12 major groundwater-depleting countries, averaged over 1971–2010. Note that data from Saudi Arabia were not used in further analysis due to the small area of crops in this country.

Table 2
Parameter Estimates of the Fixed-Effects Cobb-Douglas Production Functions and Their Significance Levels for the Five Crops Analyzed

Parameter	Wheat	Potato	Maize	Rice	Citrus
γ_A	−0.045	0.361***	0.702***	0.131**	0.270***
γ_{GW}	−0.013	0.143***	0.403***	0.072**	0.006
γ_{IW}	0.111*	0.314***	0.190***	0.097*	0.110
γ_E	0.254***	0.086**	0.136***	0.146***	0.364***
γ_t	0.136***	0.142***	0.224***	0.063***	−0.098***
γ_0	5.170***	0.086	−8.324***	3.803***	2.568**
R^2_{adj}	0.908	0.883	0.914	0.942	0.9297
Country-specific fixed effects					
China	0.24	−1.28	−1.82	−0.21	−1.56
Egypt	0.31	0.64	2.46	0.64	−0.34
India	0.13	−0.81	−1.56	−0.81	—
Iran	−0.53	−0.58	2.50	−0.19	−0.18
Italy	−0.06	0.25	0.58	0.16	−0.21
Mexico	0.33	0.33	−1.94	0.07	−0.47
Pakistan	0.00	−0.62	−0.25	−0.47	0.13
South Africa	−0.55	0.76	−0.98	−0.25	0.66
Spain	−0.15	0.53	1.50	0.50	0.73
Turkey	0.11	0.21	0.99	0.41	1.12
United States	0.18	0.14	−1.71	0.16	0.49

Note. The subscripts *A*, *GW*, *IW*, *E*, and *t* refer to land, green water, irrigation water (sum of blue water and nonrenewable groundwater), energy input, and time trend, respectively. In the fixed-effects estimation, e_{it} (equation (13)) is estimated as $u_i + v_{it}$, where u_i is the country fixed effect and v_{it} the residual. In the fixed-effects model, u_i are formally fixed—they have no distribution.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

diminishing returns with the inputs. As a consequence, we chose to use the simpler Cobb-Douglas function. Note that by applying the Cobb-Douglas function, we assume that a specific crop production function has identical curvature in all countries. For this function, the output elasticities are identical to the parameter estimates for all inputs, except for "Land" because a yield function is estimated. Hausman's specification test (Greene, 2002) was used to test if the fixed-effects model or random-effects model is appropriate (Verbeek, 2012). Hausman's test indicated that the fixed-effects model was most appropriate for all crops. The (country) fixed-effects term can be interpreted as the yield differences between countries attributable to factors not included in the production function.

The resulting production function has the following form:

$$\ln\left(\frac{Y_{it}}{A_{it}}\right) = \gamma_0 + \gamma_A \ln A_{it} + \gamma_{GW} \ln\left(\frac{GW_{it}}{A_{it}}\right) + \gamma_{IW} \ln\left(\frac{IW_{it}}{A_{it}}\right) + \gamma_E \ln\left(\frac{E_{it}}{A_{it}}\right) + \gamma_t \ln t + e_{it}, \quad (13)$$

where

$i = 1,..,11$ country index and $t = 1,..,40$ time index (1971–2010)

- Y_{it} total production (kg/year) given crop;
- GW_{it} green water (m^3/year);
- IW_{it} irrigation water (sum of blue water and nonrenewable groundwater; m^3/year);
- E_{it} energy input (kg of oil equivalent per year) assumed the same for each crop for a given country;
- e_{it} stochastic disturbance. In the fixed effects estimation e_{it} is estimated as $u_{\text{i}} + v_{\text{it}}$, where u_i is the country fixed effect. In the country fixed-effects model, the u_{i} are formally fixed—they have no distribution.

The resulting parameter estimates are given in Table 2. The significance levels of the estimated parameters are generally high, except for citrus, where both the output elasticities of *GW* and *IW* are subject to larger uncertainty. Therefore, we have to treat estimated shadow prices for citrus with care. As can be seen from the R^2 values in Table 2 and the scatterplots in Figure 3, the estimated production functions provide satisfactory predictions of the yields across countries and crops. Exceptions are potatoes in Pakistan and Mexico that show systematic deviations from the general form fitted.

Tables S4–S8 (supporting information) show the results of leaving out or adding specific variables in the Cobb-Douglass model (equation (13)). We also tested if including a time fixed effect would improve the model and affect results, as well as adding gross domestic product (GDP) per capita (which may capture differences in yield development across countries in the research period), one of the few potentially relevant variables additionally available for all countries and every year. The *F* test shows that country fixed effects improve the model. Clearly, without the country fixed-effects term, the parameter estimates are very different, because without it the model does not allow for country-specific yield levels that are considerable as can be seen from Figure 3. When the country fixed effect is eliminated, the parameter estimates of irrigation water *IW* and energy use *E* are higher than those in the preferred model, because they take up part of the between-country variance. The *F* test reveals that *E* contributes significantly to the explanatory power of the equation. The parameter estimate of *IW* and *t* are higher if energy is eliminated as *IW* and *t* take up part of the variation of the energy variable. The same applies to the time trend *t* for which the *F* test also shows that it improves the model. If all potential explanatory variables were included, the time trend describes the technological development. It also takes up the variation in time of omitted variables (e.g., an increase of fertilizer and pesticide use with time). If the time trend is omitted, the parameter estimates of *IW* and *E* increase for all crops, taking up variation that would otherwise be described by *t*. Results also show that, except for potato, including a time fixed-effect term does not significantly improve the model, although it has some effects on the estimated parameter values. Including GDP per capita hardly changes the parameter estimates and, except for wheat, does not improve explanatory power of the model.

In order to test whether model specification equation (13) is susceptible to multicollinearity, the variance inflation factor was computed for all crops and all independent variables (Table S9 supporting information). Results show that for rice some concern exists with respect to multicollinearity, while it is not an issue for the other crops.

The results of the analyses represented in Tables S4–S9 show that omitted variable bias cannot be completely ruled out. However, if country fixed effect and time trend are included, adding additional variables such as time fixed effect or GDP per capita do not further improve the model's ability to explain the data and have only a limited effect on parameter estimates. Also, the variance inflation factor shows that multicollinearity is not a big issue, and from this perspective our results are robust.

The estimated production functions relating yield to water consumption (under constant mean nominal values of the other factors) are shown in Figure 4. Clearly, for each crop, yields are substantially different between countries for the same amount of irrigation water, indicating large differences in water productivity. These differences can be attributed by differences in technology, climate (temperature, length of the growing season, and green water availability), soil fertility, and irrigation efficiency.

3.3. Estimated Shadow Prices

Based on the parameter estimates, predicted yield, irrigation water consumption, and crop price, for each year, country, and crop, the shadow price was calculated using the derivative of equations (13) and equation (5). Crop prices were available only for the years 1991–2010 for all crops and countries (Table S1; supporting information Data). The average shadow prices of irrigation water over the periods 2006–2010 and 1991–2010 for the five crops and 11 countries are presented in Table 3. Also shown are the standard deviations over these periods as a measure of year-to-year variability. As can be seen, the shadow price for citrus is highest among the crops considered for six out of the 11 countries, and for three countries it is maize. However, it should be noted that the shadow price of maize in Egypt is very high, which is the result of the very limited amount of irrigation water used for maize. Also, the results for citrus should be interpreted with care due to the uncertainty in the estimates of the elasticity coefficient for *IW*. In eight out of 11 counties rice has the smallest shadow price, while for the other three countries it is wheat. Averaged over all countries, citrus gives the highest shadow price and rice the lowest. These results are as expected as citrus trees are an expensive crop where efficient water use is the norm, while rice is a staple crop that is sold on local and regional

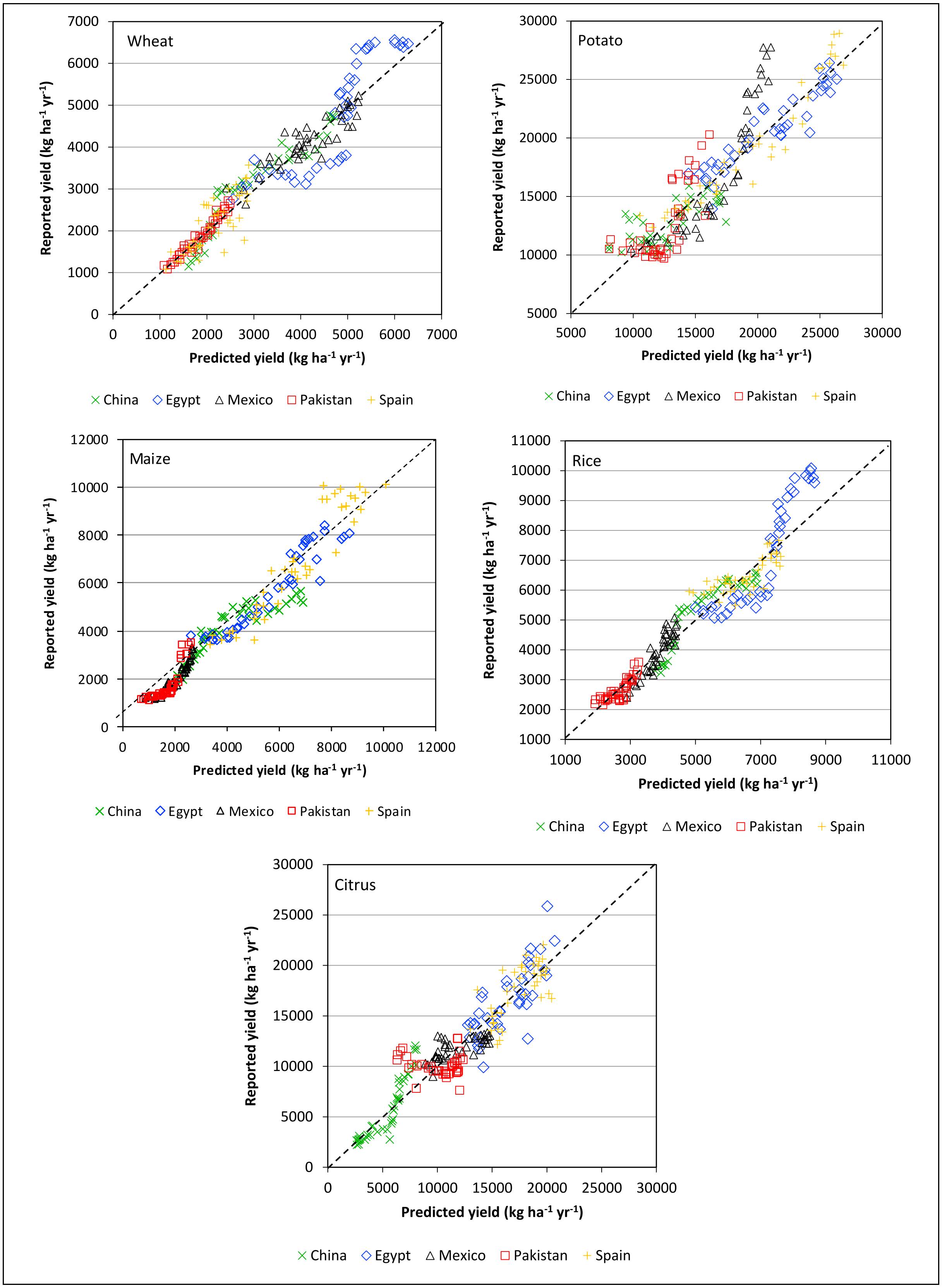

Figure 3. Scatterplots of estimated (using equation (13)) and observed yields for five countries and five crops.

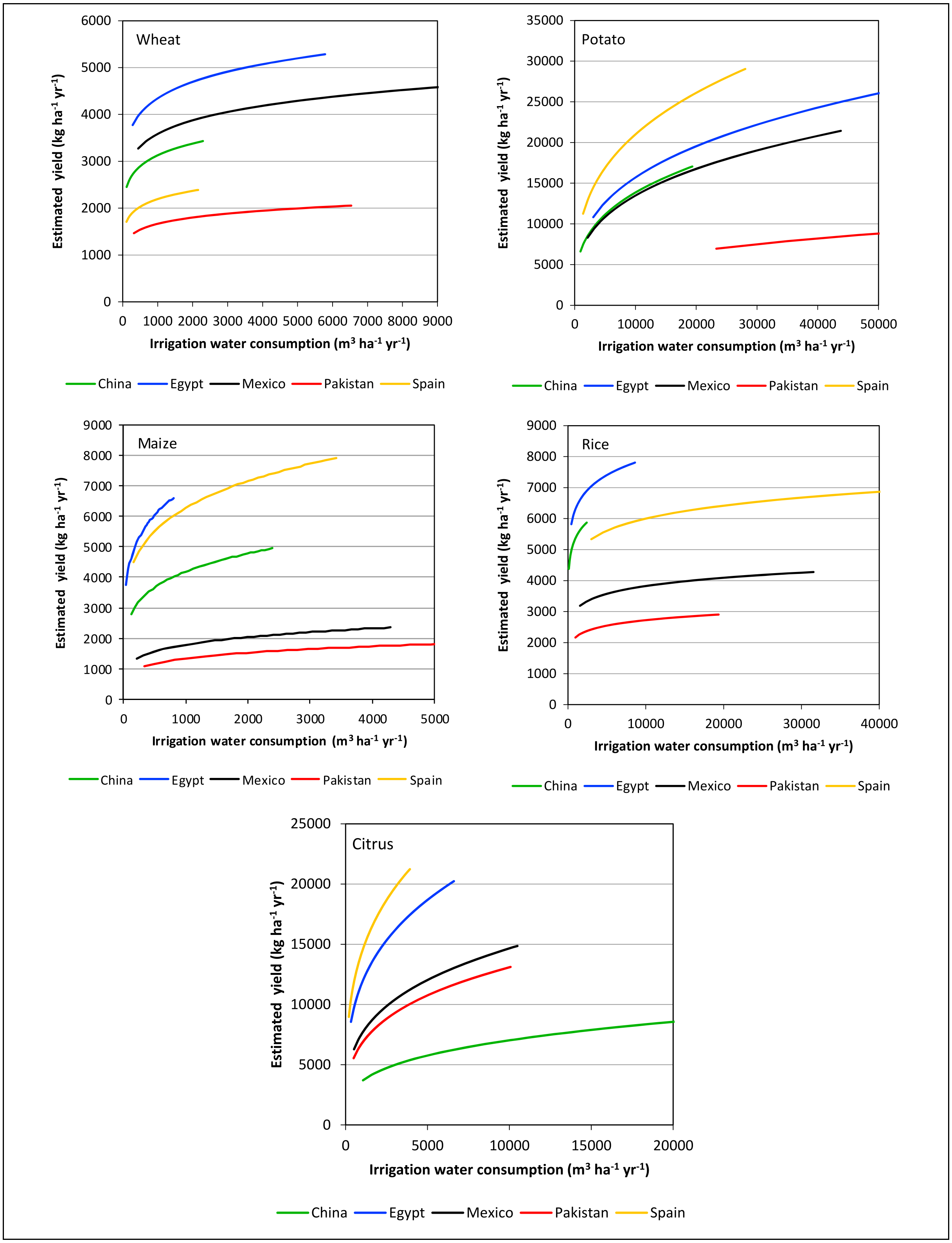

Figure 4. Parameterized (fitted) production functions (equation (13) with parameters from Table 1) for five countries and five crops. We plotted these functions only up to the maximum irrigation water use per hectare for a given crop and country.

Table 3
Average Shadow Prices of the Five Crops in the 11 countries (in $US/m^3) Over the Periods 2006–2010 and 1991–2010

Country	Wheat Avg	Wheat Std	Potato Avg	Potato Std	Maize Avg	Maize Std	Rice Avg	Rice Std	Citrus Avg	Citrus Std
2006–2010										
China	0.075	0.017	0.124	0.038	0.242	0.057	0.113	0.017	0.290	0.047
Egypt	0.096	0.027	0.066	0.009	0.870[a]	0.131[a]	0.061	0.061	0.155	0.053
India	0.032	0.004	0.031	0.002	0.033	0.027	0.103	0.103	—[c]	—[c]
Iran	0.041	0.013	0.034	0.006	0.258	0.078	0.014	0.014	0.162	0.038
Italy	0.074	0.020	0.088	0.010	0.165	0.029	0.025	0.025	0.454	0.040
Mexico	0.022	0.007	0.156	0.022	0.053	0.009	0.004	0.004	0.081	0.018
Pakistan	0.018	0.004	0.008	0.002	0.040	0.005	0.000[b]	0.000	0.058	0.011
South Africa	0.038	0.009	0.113	0.023	0.063	0.009	<0.001	0.000	0.306	0.067
Spain	0.057	0.020	0.091	0.022	0.199	0.035	0.010	0.010	0.384	0.083
Turkey	0.062	0.009	0.043	0.006	0.157	0.019	0.004	0.004	1.158[a]	0.169[a]
USA	0.064	0.014	0.054	0.010	0.299	0.198	0.013	0.013	0.113	0.052
Average	0.052	0.013	0.073	0.014	0.151	0.047	0.032	0.023	0.223	0.041
1991–2010										
China	0.058	0.016	0.073	0.038	0.182	0.101	0.105	0.033	0.160	0.089
Egypt	0.060	0.026	0.048	0.016	0.584[a]	0.195	0.043	0.043	0.095	0.045
India	0.023	0.006	0.022	0.006	0.028	0.014	0.054	0.054	—[c]	—[c]
Iran	0.066	0.093	0.048	0.054	0.179	0.115	0.027	0.027	0.090	0.048
Italy	0.065	0.023	0.075	0.013	0.141	0.027	0.017	0.017	0.368	0.100
Mexico	0.018	0.006	0.116	0.033	0.040	0.010	0.004	0.004	0.066	0.021
Pakistan	0.013	0.004	0.006	0.002	0.023	0.011	0.003[b]	0.003	0.043	0.015
South Africa	0.032	0.009	0.082	0.027	0.049	0.017	<0.001	0.000	0.193	0.081
Spain	0.044	0.016	0.089	0.032	0.161	0.041	0.009	0.009	0.317	0.074
Turkey	0.049	0.013	0.039	0.008	0.091	0.042	0.002	0.002	0.732	0.290
USA	0.046	0.015	0.044	0.010	0.138	0.138	0.008	0.008	0.056	0.042
Average	0.043	0.021	0.058	0.022	0.147	0.065	0.025	0.018	0.212	0.073

[a]Estimates are high (not used in calculating crop average) as a result of very low irrigation water use for these crops. [b]Estimates based on 1991–2002 due to lack of yield or price data in later years. [c]No estimate due to lack of yield and or price data.

Table 4
Overview of Crop-Specific Shadow Prices (in $US) Found in the Literature

Source	Region	Method used	Type of shadow price	Price ($US/m^3)
Cai et al. (2003)	Syr Darya River basin in Central Asia	Integrated hydrologic-agronomic-economic model	Marginal value of water	Wheat–maize = 0.094
He et al. (2007)	China	Dynamic computable general equilibrium	Marginal value of water	Different sectors = 0.52
Hellegers and Perry (2004)	Kemry (Egypt) 2001–2003		Residual method	Rice = 0.06 Wheat = 0.14 Maize = 0.07
Hellegers and Perry (2004)	Haryana (India) 2001–2003		Residual method	Rice = 0.035 Maize = 0.095
Hellegers and Davidson (2010)	Musi sub-basin (India) 2001-2002		Residual method	Rice = 0.003 Maize = 0.254
Berbel et al. (2010)	Guadalquivir Basin (Spain) 2005		Residual method	Wheat = 0.10 Maize = 0.09 Rice = 0.05 Citrus = 0.43
Williams et al. (2017)	Ogallala Aquifer (Texas, NM, USA) 2004	Single-cell aquifer analysis following Gisser and Sánchez (1980)	Marginal value of water left in the ground (co-state intertemporal optimization)	Wheat = 0.10 Maize = 0.15

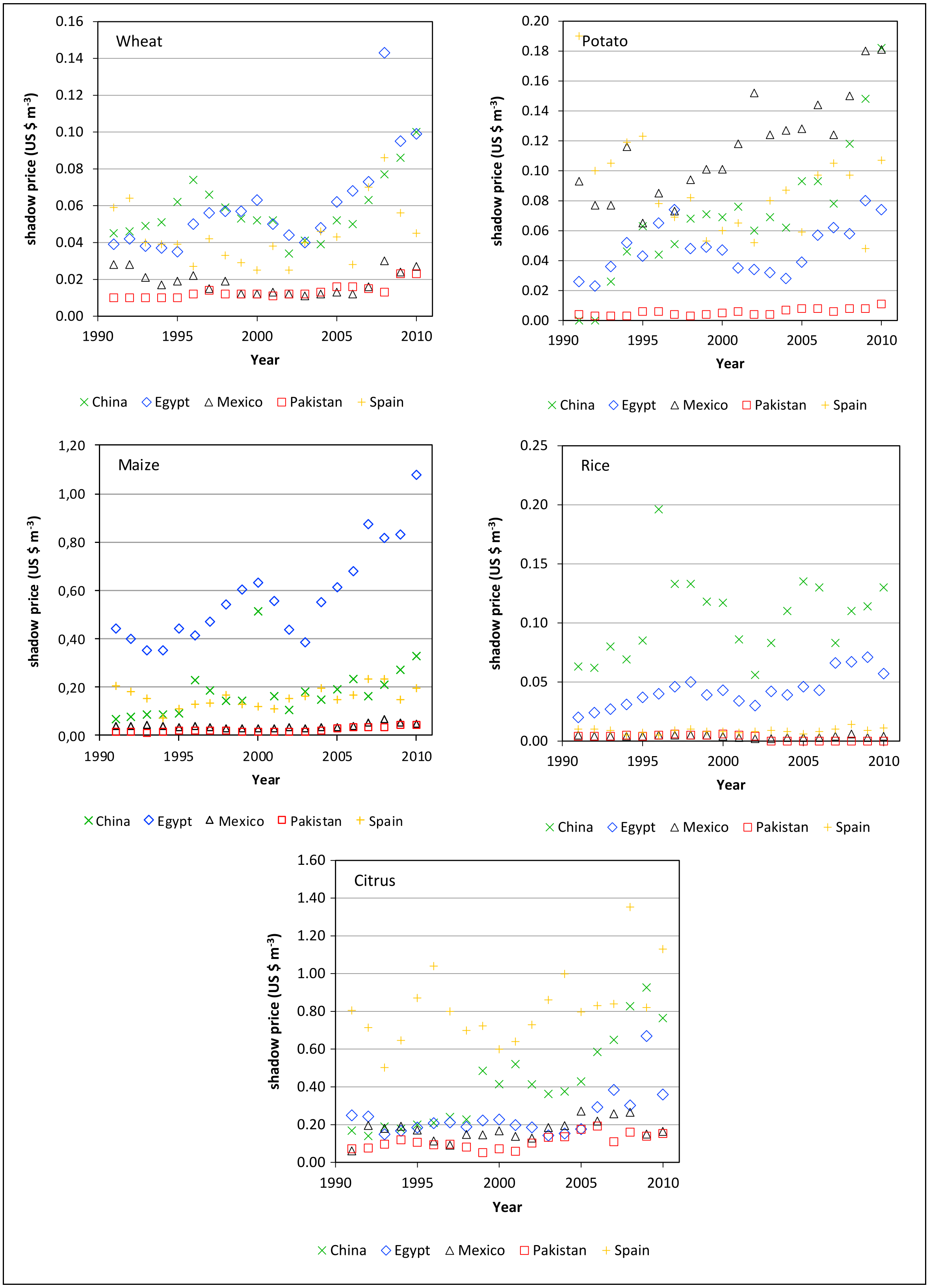

Figure 5. Time series of estimated shadow prices for five countries and five crops over the period 1991–2010.

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Table 5
Increase in Revenue ($US·ha^{-1}·year^{-1}) and Reduction in Irrigation Water Consumption (m^3·ha^{-1}·year^{-1}) when Reallocating a Substantial Amount of Irrigation Water Consumption (Limited by Half of the Nonrenewable Groundwater Consumption) Between Crops With the Aim of Either Maximizing Revenue or Minimizing Nonrenewable Groundwater Consumption

Country	From crop 1	To crop 2	$\Delta R_{1\rightarrow 2}$ ($US·ha^{-1}·year^{-1})	$\Delta IW_{1\rightarrow 2}$ (m^3·ha^{-1}·year^{-1})
China	Wheat	Maize	114	115
Egypt	Rice	Maize	6.6	86
India	Maize	Wheat	8.8	134
Iran	Wheat	Potato	367	577
Italy	Rice	Potato	22	212
Mexico	Rice	Potato	327	3,895
Pakistan	Rice	Wheat	23	1,593
South Africa	Rice	Potato	35	25
Spain	Rice	Potato	9.1	41
Turkey	Rice	Potato	68	194
United States	Wheat	Potato	19	21

markets at low prices and is mostly grown under paddy irrigation with large evaporation water losses (i.e., flood irrigation with low irrigation efficiency).

Differences between countries are also considerable. Pakistan has the lowest shadow prices for wheat, potato, maize, and citrus and has a low price for rice, while shadow prices in India are relatively low throughout as well. This can be explained by relatively low water productivity in these countries and relatively low food prices. This result can be further explained by the fact that groundwater pumping is subsidized by the government in India particularly. The different crop prices and different water use efficiencies between countries make it difficult to make inferences about efficiency by comparing shadow prices between countries. As prices and water use efficiencies are more alike within a country, it is safer to assume that the dispersion of shadow prices between crops within a country is more informative. For instance, the relatively low shadow price of rice in Pakistan compared with that of maize and wheat indicates inefficient use of irrigation water, including nonrenewable groundwater. Similarly, shadow prices reveal inefficient use of irrigation water for rice in Italy, Mexico, South Africa, Spain, Turkey, and the United States, while in Egypt allocating water to maize may help to improve the efficiency of irrigation water use. The inefficiencies thus identified by differences in shadow prices can be a basis for improving efficiency by reallocating irrigation water (see section 3.4). One should, however, be careful with these comparisons due to the heterogeneity of conditions especially within large countries. Other factors aside from water, such as elevation, climate, and soil type, may dictate that a certain crop can only be grown in a limited part of the country, which prohibits an increase in efficiency by changing crops. Also, certain countries have multicropping, with wheat growing in the colder and wetter season and rice in the drier season, resulting in lower shadow prices for irrigation water applied to rice.

Table 4 shows shadow prices of water found in the literature. Shadow prices of water for agricultural crop production are found roughly to be between 0.01 and 0.25 $US/m^3, with most estimated prices smaller than 0.10 $US/m^3. If other sectors are included in the analysis, shadow prices are found to be higher. The estimated shadow prices in our analysis (Table 3) are in line with prices found in literature, except for maize in Egypt where we find very high values compared to those in Hellegers and Perry (2004).

Figure 5 shows the time series of the estimated shadow prices for five countries and five crops over the period 1991–2010. The different absolute levels of each time series reflect the difference in average shadow prices between countries (Table 3), while the year-to-year fluctuations are also considerable (see also the standard deviations in Table 3). These fluctuations are caused by year-to-year variability in climate and market prices. Also, the time series clearly show a positive trend for many of the shadow prices. The water consumption time series do not show a clear trend, however, while the increase in yield with time is incorporated in the model. This means that these trends are predominantly caused by increases in crop (food) prices over the period considered. Note that the order from highest to lowest shadow prices between countries is different from the order of production curves (Figure 4). This is the result from the difference in crop market prices between countries.

Table 6
Increase in Revenue (M$US/year) and Reduction in Irrigation Water Consumption (MCM/year) When Reallocating a Substantial Amount of Irrigation Water Consumption Between Crops With the Aim of Either Maximizing Revenue or Minimizing Nonrenewable Groundwater Consumption

Country	From crop 1	To crop 2	$\Delta R_{1\rightarrow 2}$ (M$US/year)	$\Delta IW_{1\rightarrow 2}$ (MCM/year)
China	Wheat	Maize	547	551
Egypt	Rice	Maize	5	62
India	Maize	Wheat	50	761
Iran	Wheat	Potato	1,798	2,827
Italy	Rice	Potato	4	41
Mexico	Rice	Potato	14	167
Pakistan	Rice	Wheat	47	3,358
South Africa	Rice	Potato	$3{\cdot}10^{-2}$	$3{\cdot}10^{-2}$
Spain	Rice	Potato	1	3
Turkey	Rice	Potato	1	4
United States	Wheat	Potato	413	459

Note. M$US = million U.S. dollar; MCM = million cubic meter.

3.4. Reallocation of Irrigation Water

Using the approach described in section 2.3, we calculated for each country the increase in revenue or the possible reduction of nonrenewable groundwater consumption when reallocating a considerable amount of irrigation water (*IW*) consumption from one staple crop to another. To prevent changes in water consumption that lie far outside the observed values, we made sure that the reallocated total volume of irrigation water consumption per hectare does not exceed half of the nonrenewable groundwater consumption of the giving or receiving crop. Note that this is just an arbitrary example to demonstrate the potential of reallocation to increase efficiency at the same level of water consumption or the reduction of nonrenewable groundwater consumption by increasing efficiency. Further economic optimization by equalizing shadow prices of all crops would be a next step, which would, however, need to involve other production factors, including land, to be really meaningful.

The change in revenue and irrigation water consumption per hectare are given in Table 5. To obtain total volumes per country, we multiplied the revenue per hectare (year 2010) with the irrigated area of the staple crop per country for which we reduced the irrigation water consumption. The results are shown in Table 6. There are some countries (South Africa and Italy) where the acreage of the crops irrigated with nonrenewable groundwater is small, so that effects on total revenue and water consumption are limited. However, in general, results show that given the current level of nonrenewable groundwater consumption, a considerable increase in revenue can be achieved for a number of countries, for example, China, Iran, and the United States, if part of the irrigation water was to be reallocated. Or alternatively, the same level of revenue could be obtained at considerable savings of irrigation water and nonrenewable groundwater consumption. This is particularly the case in Pakistan, Iran, and the United States, where this limited reallocation exercise would save a volume of water that amounts to respectively 9%, 9%, and 6% of these countries' total nonrenewable groundwater consumption. In particular, rice seems to be the crop for which irrigation water is less efficiently applied. The differences among the countries are large, depending on their irrigation water consumption.

4. Discussion and Conclusions

We estimated shadow prices for irrigation water used for five major crops in 11 countries with considerable groundwater depletion. The shadow price as defined in our study represents the current marginal value created with irrigation water. As a result, it is an indication for the efficient use of irrigation water, and, as we focus on groundwater depleting countries, prudent or wasteful use of nonrenewable groundwater. Our results reveal large differences in shadow prices for different crops within a country. This shows that there is a great opportunity for more efficient use of irrigation water and nonrenewable groundwater within these countries by considering a different allocation of water over crops. The economic analysis is based on considering the use of water at the margin, using the characteristics of the production function (diminishing marginal returns on water). The shadow price itself, being a measure of marginal return, can provide an indication on how changing water allocation can be profitable, but a full consideration of the revenue function (see Figure 1) is needed to estimate the effects of large water reallocations. Moreover, as water, and particularly groundwater, is mostly locally available and cannot be easily transported over large distances, reallocation of nonrenewable groundwater between crops would inevitably lead to changing the cropping pattern in a country. Also, large changes of production volumes of crops within a country may affect local prices that has not been taken into account. In this sense, the results in Tables 5 and 6 are a first-order estimate of the effects of reallocating nonrenewable groundwater.

The shadow prices for a given crop differ quite a lot between countries. Although it is generally difficult to compare between countries due to differences in crop prices and water use efficiencies, shadow prices for countries that use large amounts of nonrenewable groundwater reflect the regionally limited value that is given to a finite resource. A global water market does not exist, but products based upon nonrenewable groundwater are traded globally. Providing a global overview of regional groundwater overuse and associated economic consequences through shadow price is an important step toward better water management strategy worldwide. Also, shadow prices could be used with water footprint tools (Mekonnen & Hoekstra, 2011) to estimate the value of virtual water used in trade and products.

Our analysis, targeting the water consumption of individual crops by water type (green water and irrigation water), is only possible using a state-of-the-art global hydrology and water resources model such as PCR-GLOBWB. We apply panel data at the national level based on the aforementioned water data and observed globally available data on crop yield, production, and price, instead of studies that apply yield data based on models.

There are obvious uncertainties in our analyses. First, as the consumptive water use estimates of green water, blue water, and nonrenewable groundwater are obtained from simulations with a global hydrological model, they are subject to considerable uncertainty; obviously, reported statistics on crop yield, prices, and water withdrawal are not without error either. Although PCR-GLOBWB can reproduce global withdrawals (Sutanudjaja et al., 2018) and groundwater depletion (Wada, van Beek, & Bierkens, 2012; Wada, van Beek, Sperna Weiland, et al., 2012), considerable uncertainty remains for given countries, specifically regarding the division between groundwater and surface water withdrawal. Repeating our analysis with similar global hydrology and water resources models such as WaterGap3 (Müller Schmied et al., 2014) and H08 (Hanasaki et al., 2018) would shed light on this uncertainty. Also, performing the analysis on the country level, albeit convenient as yield and price data are available at this level of aggregation, neglects large regional differences in groundwater and surface water use as well as crop mix composition. This may lead to both overestimation and underestimation of the shadow price for a given crop. Finally, the econometric model used has its limitations when applied at the global level. First, we apply a concave Cobb-Douglas production function through all the country-crop combinations, assuming that this functional form fits crop production in all 11 countries. Second, due to limited data availability, next to the water inputs, we are only able to include land and energy input in the model. Although it was shown to be limited, bias in parameter estimates related to omitted variables such as capital, labor, and fertilizer cannot be ruled out entirely.

When considering improvements and extensions of our approach, several come to mind. An obvious first step is to repeat our analysis at the finer spatial level, for example, calculating shadow prices per crop at the 5-arcmin cells of our global hydrological model PCR-GLOBWB. This would allow the explicit consideration of the regional differences in water sources used as well as the associated crops grown, with better estimates of shadow prices as a result. At the same time, the overuse of surface water could also be included in the analysis (Wada & Bierkens, 2014). Of course, this extension is only possible if crop yield and input data are available on a grid-scale basis using a crop growth or production model (with their assumptions). A higher-resolution gridded approach would also help to resolve within-country heterogeneity of other production factors such as climate, soil fertility, and labor availability. Obviously, one still has to cope with other unknowns such as capital and several variable inputs such as fertilizer and pesticides. A logical addition would be the inclusion of other sectoral water requirements (domestic and industry) and calculate associated shadow prices. This would allow the optimal allocation of scarce groundwater between sectors, further maximizing net profit.

Given the nature of nonrenewable groundwater as a resource that is being depleted, another necessary extension is including the temporal dimension in our definition of shadow price or economically efficient reallocation. When looking for efficient alternatives for groundwater use, intertemporal efficiency should be considered (Burt, 1964; Gisser & Sánchez, 1980; Koundouri et al., 2017; Negri, 1989; Steward et al., 2013). This requires not only discounting but also additional assumptions about future prices and productivity. Moreover, as depleting groundwater and associating deeper groundwater levels result in increased extraction costs (Foster et al., 2015), an extraction cost model with technological capacity should also be included, as well as including the economic lifetime of nonrenewable groundwater assets. This can only be done realistically by including a groundwater flow model.

In order to arrive at economically efficient allocation of groundwater resources, a more elaborate water-cost model is also needed. Apart from extraction and distribution costs, such a water-cost model would also include current and future opportunity costs and preferably also environmental and economic externalities. The combination of shadow pricing with such a water-cost model would allow to search for the allocation of both blue water and nonrenewable groundwater for which net societal benefits are maximized with minimal depletion rates; note that economically efficient use of groundwater resources may involve some degree of depletion. If regionally observed yield data and inputs are available, regional differences can be included in the econometric model, allowing for better estimation of the shadow price. This framework would also be suitable to optimize investments in water-saving technology or increasing water supply.

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References

Baltagi, B. (2008). *Econometric analysis of panel data*. New York: John Wiley.

Berbel, J., Mesa-Jurado, M. A., & Pistón, J. M. (2011). Value of irrigation water in Guadalquivir Basin (Spain) by residual value method. *Water Resources Management*, *25*(6), 1565–1579. https://doi.org/10.1007/s11269-010-9761-2

Boisvert, R. N. (1982). The translog production function: Its properties, its several interpretations and estimation problems. Cornell University, Department of Applied Economics and Management.

Burt, O. R. (1964). Optimal resource use over time with an application to ground water. *Management Science*, *11*(1), 80–93. https://doi.org/10.1287/mnsc.11.1.80

Burt, O. R. (1967). Temporal allocation of groundwater. *Water Resources Research*, *3*(1), 45–56. https://doi.org/10.1029/WR003i001p00045

Cai, X., McKinney, D. C., & Lasdon, L. S. (2003). Integrated hydrologic-agronomic-economic model for river basin management. *Journal of Water Resources Planning and Management*, *129*(1), 4–17. https://doi.org/10.1061/(ASCE)0733-9496(2003)129:1(4)

Chambers, R. G. (1988). *Applied production analysis: A dual approach*. Cambridge UK: Cambridge University Press.

Christensen, L. R., Jorgenson, D. W., & Lau, L. J. (1973). Transcendental logarithmic production frontiers. *The Review of Economics and Statistics*, *55*(1), 28–45. https://doi.org/10.2307/1927992

Colby, B. G. (1989). Estimating the value of water in alternative uses. *Natural Resources Journal*, 511–527. https://doi.org/10.1029/96WR00076/pdf

De Graaf, I. E., van Beek, L. P. H., Gleeson, T., Moosdorf, N., Schmitz, O., Sutanudjaja, E. H., & Bierkens, M. F. P. (2017). A global-scale two-layer transient groundwater model: Development and application to groundwater depletion. *Advances in Water Resources*, *102*, 53–67. https://doi.org/10.1016/j.advwatres.2017.01.011

Dinar, A., Pochat, V., & Albiac-Murillo, J. (Eds.) (2015). Water pricing experiences and innovations. In *Global Issues in Water Policy* (Vol. 9, p. 471). Cham (Switzerland): Springer International Publishers.

Elnaboulsi, J. C. (2001). Nonlinear pricing and capacity planning for water and wastewater services. *Water Resources Management*, *15*(1), 55–69. https://doi.org/10.1023/A:1012228611303

Esteban, E., & Albiac, J. (2011). Groundwater and ecosystems damages: Questioning the Gisser–Sánchez effect. *Ecological Economics*, *70*(11), 2062–2069. https://doi.org/10.1016/j.ecolecon.2011.06.004

Famiglietti, J. (2014). The global groundwater crisis. *Nature Climate Change*, *4*(11), 945–948. https://doi.org/10.1038/nclimate2425

Food and Agriculture Organization of the United Nations (2016a). Crop statistics: Production. Retrieved from http://www.fao.org/faostat/en/#data/QC

Food and Agriculture Organization of the United Nations (2016b). Price statistics: Producer prices—Annual. Retrieved from http://www.fao.org/faostat/en/#data/PP

Foster, T., Brozovic, N., & Butler, A. P. (2015). Analysis of the impacts of well yield and groundwater depth on irrigated agriculture. *Journal of Hydrology*, *523*, 86–96. https://doi.org/10.1016/j.jhydrol.2015.01.032

Frank, R. H. (2010). *Microeconomics and behavior* (8th ed.). New York: The McGraw-Hill Companies, Inc.

Gisser, M., & Sánchez, D. (1980). Competition versus optimal control in groundwater pumping. *Water Resources Research*, *16*(4), 638–642. https://doi.org/10.1029/WR016i004p00638

Gleeson, T., Befus, K. M., Jasechko, S., Luijendijk, E., & Bayani Cardenas, M. (2016). The global volume and distribution of modern groundwater. *Nature Geoscience*, *9*(2), 161–167. https://doi.org/10.1038/ngeo2590

Gleeson, T., Wada, Y., Bierkens, M. F. P., & van Beek, L. P. H. (2012). Water balance of global aquifers revealed by groundwater footprint. *Nature*, *488*(7410), 197–200. https://doi.org/10.1038/nature11295

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., et al. (2010). Food security: The challenge of feeding 9 billion people. *Science*, *327*(5967), 812–818. https://doi.org/10.1126/science.1185383

Greene, W. H. (2002). *Econometric analysis* (5th ed.). Upper Saddle River, NJ: Prentice Hall.

Haddeland, I., Heinke, J., Biemans, H., Eisner, S., Flörke, M., Hanasaki, N., et al. (2013). Global water resources affected by human interventions and climate change. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3251–3256. https://doi.org/10.1073/pnas.1222475110

Hanasaki, N., Yoshikawa, S., Pokhrel, Y., & Kanae, S. (2018). A global hydrological simulation to specify the sources of water used by humans. *Hydrology and Earth System Sciences*, *22*(1), 789–817. https://doi.org/10.5194/hess-22-789-2018
He, J., Chen, X., Shi, Y., & Li, A. (2007). Dynamic computable general equilibrium model and sensitivity analysis for shadow price of water resource in China. *Water Resources Management*, *21*(9), 1517–1533. https://doi.org/10.1007/s11269-006-9102-7
Hellegers, P. J. G. J., & Davidson, B. (2010). Determining the disaggregated economic value of irrigation water in the Musi sub-basin in India. *Agricultural Water Management*, *97*(6), 933–938. https://doi.org/10.1016/j.agwat.2010.01.026
Hellegers, P. J. G. J., & Perry, C. J. (2004). *Water as an economic good in irrigated agriculture: Theory and practice*, *Report Series 29109*. Wageningen, The Netherlands: Wageningen University and Research Center, Agricultural Economics Research Institute.
Immerzeel, W. W., Stoorvogel, J., & Antle, J. (2008). Can payments for ecosystem services save the water tower of Tibet? *Agricultural Systems*, *96*(1-3), 52–63. https://doi.org/10.1016/j.agsy.2007.05.005
Jia, S., Long, Q., & Liu, W. (2016). The fallacious strategy of virtual water trade. *International Journal of Water Resources Development*, *33*(2), 340–347. https://doi.org/10.1080/07900627.2016.1180591
Kaiser, B., & Roumasset, J. (2002). Valuing indirect ecosystem services: the case of tropical watersheds. *Environment and Development Economics*, *7*(04), 701–714. https://doi.org/10.1017/S1355770X02000426
Kiani, A. R., & Abbasi, F. (2012). *Optimizing water consumption using crop water production functions*. London, UK: INTECH Open Access Publisher.
Konikow, L. F. (2011). Contribution of global groundwater depletion since 1900 to sea-level rise. *Geophysical Research Letters*, *38*, L17401. https://doi.org/10.1029/2011GL048604
Koundouri P. (2000). Three approaches to measuring natural resource scarcity: Theory and application to groundwater. PhD thesis Department of Economics, Faculty of Economics and Politics, University of Cambridge, Cambridge, U.K.
Koundouri, P. (2004). Current issues in the economics of groundwater resource management. *Journal of Economic Surveys*, *18*(5), 703–740. https://doi.org/10.1111/j.1467-6419.2004.00234.x
Koundouri, P., Roseta-Palma, C., & Englezos, N. (2017). Out of sight, not out of mind: Developments in economic models of groundwater management. *International Review of Environmental and Resource Economics*, *11*(1), 55–96. https://doi.org/10.1561/101.00000091
Ku, S. J., & Yoo, S. H. (2012). Economic value of water in the Korean manufacturing industry. *Water Resources Management*, *26*(1), 81–88. https://doi.org/10.1007/s11269-011-9905-z
Lehner, B., Reidy Liermann, C., Revenga, C., Vörösmarty, C., Fekete, B., Crouzet, P., et al. (2011). High- resolution mapping of the world's reservoirs and dams for sustainable river-flow management. *Frontiers in Ecology and the Environment*, *9*(9), 494–502. https://doi.org/10.1890/100125
Liu, X., Chen, X., & Wang, S. (2009). Evaluating and predicting shadow prices of water resources in China and its nine major river basins. *Water Resources Management*, *23*(8), 1467–1478. https://doi.org/10.1007/s11269-008-9336-7
Medellín-Azuara, J., Howitt, R. E., & Harou, J. J. (2012). Predicting farmer responses to water pricing, rationing and subsidies assuming profit maximizing investment in irrigation technology. *Agricultural Water Management*, *108*, 73–82. https://doi.org/10.1016/j.agwat.2011.12.017
Mekonnen, M. M., & Hoekstra, A. Y. (2011). The green, blue and grey water footprint of crops and derived crop products. *Hydrology and Earth System Sciences*, *15*(5), 1577–1600. https://doi.org/10.5194/hess-15-1577-2011
Mesa-Jurado, M. A., Berbel, J., & Orgaz Rosua, F. (2010). Estimating marginal value of water for irrigated olive grove with the production function method. *Spanish Journal of Agricultural Research*, *8*(S2), 197–S206. https://doi.org/10.5424/sjar/201008S2-1362
Müller Schmied, H., Eisner, S., Franz, D., Wattenbach, M., Portmann, F. T., Flörke, M., & Döll, P. (2014). Sensitivity of simulated global-scale freshwater fluxes and storages to input data, hydrological model structure, human water use and calibration. *Hydrology and Earth System Sciences*, *18*(9), 3511–3538. https://doi.org/10.5194/hess-18-3511-2014
Negri, D. H. (1989). The common property aquifer as a differential game. *Water Resources Research*, *25*(1), 9–15. https://doi.org/10.1029/WR025i001p00009
Oki, T., & Kanae, S. (2006). Global hydrological cycles and world water resources. *Science*, *313*(5790), 1068–1072. https://doi.org/10.1126/science.1128845
Organisation for Economic Cooperation and Development (2015). Environment at a glance 2015: OECD indicators. Retrieved from www.oecd-ilibrary.org/environment/environment-at-a-glance-2015_9789264235199-en
Perrone, D., & Jasechko, S. (2017). Dry groundwater wells in the western United States. *Environmental Research Letters*, *12*(10), 104002. https://doi.org/10.1088/1748-9326/aa8ac0
Portmann, F. T., Siebert, S., & Döll, P. (2010). MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. *Global Biogeochemical Cycles*, *24*, GB1011. https://doi.org/10.1029/2008GB003435
Richey, A. S., Thomas, B. F., Lo, M., Reager, J. T., Famiglietti, J. S., Voss, K., et al. (2015). Quantifying renewable groundwater stress with GRACE. *Water Resources Research*, *51*, 5217–5238. https://doi.org/10.1002/2015WR017349
Rinaudo, J.-D., Neverre, N., & Montginoul, M. (2012). Simulating the impact of pricing policies on residential water demand: a southern France case study. *Water Resources Management*, *26*(7), 2057–2068. https://doi.org/10.1007/s11269-012-9998-z
Rogers, P., Bhatia, R., & Huber-Lee, A. (1998). Water as a social and economic good: How to put the principle into practice. (Working paper). TAC Background Papers no. 2, Global Water Partnership/Swedish International Development Agency, Stockholm, Sweden, 40 pp.
Steward, D. R., Bruss, P. J., Yang, X., Staggenborg, S. A., Welch, S. M., & Apley, M. D. (2013). Tapping unsustainable groundwater stores for agricultural production in the High Plains Aquifer of Kansas, projections to 2110. *Proceedings of the National Academy of Science U.S.A.*, *110*(37), E3477–E3486. https://doi.org/10.1073/pnas.1220351110
Sutanudjaja, E. H., van Beek, R., Wanders, N., Wada, Y., Bosmans, J. H. C., Drost, N., et al. (2018). PCR-GLOBWB 2: A 5 arc-minute global hydrological and water resources model. *Geoscientific Model Development*, *11*(6), 2429–2453. https://doi.org/10.5194/gmd-11-2429-2018
Tilman, D., Balzer, C., Hill, J., & Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(50), 20,260–20,264. https://doi.org/10.1073/pnas.1116437108
To, P. X., Dressler, W. H., Mahanty, S., & Pham, T. T. (2012). The prospects for payment for ecosystem services (PES) in Vietnam: A look at three payment schemes. *Human Ecology*, *40*(2), 237–249. https://doi.org/10.1007/s10745-012-9480-9
Tsur, Y., & Graham-Tomasi, T. (1991). The buffer value of groundwater with stochastic surface water supplies. *Journal of Environmental Economics and Management*, *21*(3), 201–224. https://doi.org/10.1016/0095-0696(91)90027-G

Valin, H., Sands, R. D., van der Mensbrugghe, D., Nelson, G. C., Ahammad, H., Blanc, E., et al. (2014). The future of food demand: Understanding differences in global economic models. *Agricultural Economics*, *45*(1), 51–67. https://doi.org/10.1111/agec.12089

Van Beek, L. P. H., Wada, Y., & Bierkens, M. F. P. (2011). Global monthly water stress: 1. Water balance and water availability. *Water Resources Research*, *47*, W07517. https://doi.org/10.1029/2010WR009791

Veninga, W. (2017). The shadow price of fossil groundwater. MSc thesis Wageningen University. Thesis online collection, WTO/2223572 (http://edepot.wur.nl/425744), 50 p.

Verbeek, M. (2012). *A guide to modern econometrics* (4th ed.). Chichester, UK: John Wiley.

Wada, Y., van Beek, L. P. H., van Kempen, C. M., Reckman, J. W. T., Vasak, S., & Bierkens, M. F. P. (2010). Global depletion of groundwater resources. *Geophysical Research Letters*, *37*, L20402. https://doi.org/10.1029/2010GL044571

Wada, Y., & Bierkens, M. F. P. (2014). Sustainability of global water use: Past reconstruction and future projections. *Environmental Research Letters*, *9*(10), 104003. https://doi.org/10.1088/1748-9326/9/10/104003

Wada, Y., van Beek, L. P. H., & Bierkens, M. F. P. (2011). Modelling global water stress of the recent past: On the relative importance of trends in water demand and climate variability. *Hydrology and Earth System Sciences*, *15*(12), 3785–3808. https://doi.org/10.5194/hess-15-3785-2011

Wada, Y., van Beek, L. P. H., & Bierkens, M. F. P. (2012). Nonsustainable groundwater sustaining irrigation: A global assessment. *Water Resources Research*, *48*, W00L06. https://doi.org/10.1029/2011WR010562

Wada, Y., van Beek, L. P. H., Sperna Weiland, F. C., Chao, B., Wu, Y.-H., & Bierkens, M. F. P. (2012). Past and future contribution of global groundwater depletion to sea-level rise. *Geophysical Research Letters*, *39*, L09402. https://doi.org/10.1029/2012GL051230

Wada, Y., Wisser, D., & Bierkens, M. F. P. (2014). Global modeling of withdrawal, allocation and consumptive use of surface water and groundwater resources. *Earth System Dynamics*, *5*(1), 15–40. https://doi.org/10.5194/esd-5-15-2014

Wada, Y., Wisser, D., Eisner, S., Flörke, M., Gerten, D., Haddeland, I., et al. (2013). Multimodel projections and uncertainties of irrigation water demand under climate change. *Geophysical Research Letters*, *40*, 4626–4632. https://doi.org/10.1002/grl.50686

Wang, H., & Lall, S. (2002). Valuing water for Chinese industries: A marginal productivity analysis. *Applied Economics*, *34*(6), 759–765. https://doi.org/10.1080/00036840110054044

Weedon, G. P., Balsamo, G., Bellouin, N., Gomes, S., Best, M. J., & Viterbo, P. (2014). The WFDEI meteorological forcing data set: WATCH Forcing Data methodology applied to ERA-Interim reanalysis data. *Water Resources Research*, *50*, 7505–7514. https://doi.org/10.1002/2014WR015638

Williams, R. B., Al-Hmoud, R., Segarra, E., & Mitchell, D. (2017). An estimate of the shadow price of water in the southern Ogallala Aquifer. *Journal of Water Resource and Protection*, *09*(03), 289–304. https://doi.org/10.4236/jwarp.2017.93019

Yaron, D. (1967). Empirical analysis of the demand for water by Israeli agriculture. *Journal of Farm Economics*, *49*(2), 461–473. https://doi.org/10.2307/1237216

Young, R. A., & Loomis, J. B. (2014). *Determining the economic value of water: Concepts and methods*. Washington, DC: Routledge.

Ziolkowska, J. R. (2015). Shadow price of water for irrigation—A case of the High Plains. *Agricultural Water Management*, *153*, 20–31. https://doi.org/10.1016/j.agwat.2015.01.024