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Key Points:

- Feed for cattle production causes groundwater stress to crucial U.S. aquifer systems
- Methodology to link groundwater use and stress to crop types for the first time
- Total uncertainty is largely due to recharge and irrigation application efficiency

Supporting Information:

- Readme
- Supporting text, tables, and figures

Correspondence to:
T. Gleeson,
tom.gleeson@mcgill.ca

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Linking groundwater use and stress to specific crops using the groundwater footprint in the Central Valley and High Plains aquifer systems, U.S.

Laurent Esnault[1], Tom Gleeson[1], Yoshihide Wada[2], Jens Heinke[3], Dieter Gerten[3], Elizabeth Flanary[1], Marc F. P. Bierkens[2,4], and Ludovicus P. H. van Beek[2]

[1]Department of Civil Engineering, McGill University, Montreal, Quebec, Canada, [2]Department of Physical Geography, Utrecht University, Utrecht, Netherlands, [3]Potsdam Institute for Climate Impact Research, Research Domain of Earth System Analysis, Potsdam, Germany, [4]Unit Soil and Groundwater Systems, Deltares, Utrecht, Netherlands

Abstract A number of aquifers worldwide are being depleted, mainly by agricultural activities, yet groundwater stress has not been explicitly linked to specific agricultural crops. Using the newly developed concept of the groundwater footprint (the area required to sustain groundwater use and groundwater-dependent ecosystem services), we develop a methodology to derive crop-specific groundwater footprints. We illustrate this method by calculating high-resolution groundwater footprint estimates of crops in two heavily used aquifer systems: the Central Valley and High Plains, U.S. In both aquifer systems, hay and haylage, corn, and cotton have the largest groundwater footprints, which highlights that most of the groundwater stress is induced by crops meant for cattle feed. Our results are coherent with other studies in the High Plains but suggest lower groundwater stress in the Central Valley, likely due to artificial recharge from surface water diversions which were not taken into account in previous estimates. Uncertainties of recharge and irrigation application efficiency contribute the most to the total relative uncertainty of the groundwater footprint to aquifer area ratios. Our results and methodology will be useful for hydrologists, water resource managers, and policy makers concerned with which crops are causing the well-documented groundwater stress in semiarid to arid agricultural regions around the world.

1. Introduction

The global rate of groundwater depletion has more than doubled since the 1960s [*Wada et al.*, 2010] and even accelerated recently over the 2000–2008 period [*Konikow*, 2011], which is driven largely by irrigation demand for agriculture [*Aeschbach-Hertig and Gleeson*, 2012]. Groundwater abstraction can result in increased recharge rates sometimes due to irrigation water return flow but more often leads to decreased groundwater discharge and/or groundwater depletion, defined as the permanent loss of stored groundwater [*Aeschbach-Hertig and Gleeson*, 2012]. Groundwater depletion occurs when groundwater abstraction exceeds the capture of groundwater by increased recharge or decreased discharge [*Bredehoeft*, 2002]. Water stress is an indicator of water scarcity for humans and is generally defined as the ratio of abstractions to surface water and groundwater availability [*Oki and Kanae*, 2006]. More recently estimations of water stress or scarcity have used consumptive use of water as opposed to abstractions, thereby giving a more accurate portrayal of freshwater depletion [*Hoekstra et al.*, 2012]. Groundwater depletion and stress have been quantified at regional to global scales [*Aeschbach-Hertig and Gleeson*, 2012; *Gleeson et al.*, 2012; *Konikow*, 2011; *Wada et al.*, 2012]. Although groundwater stress is often due to agriculture, it has yet to be explicitly linked to specific crops.

Blue water is the crucial freshwater resource comprised of surface water such as lakes or rivers and groundwater in aquifers [*Falkenmark and Rockstrom*, 2006]. Though ~85% of global crop water consumption originates from green water resources (the rainwater stored in the soil as soil moisture) [*Rost et al.*, 2008], agriculture consumes most of the groundwater abstracted, and groundwater accounts for ~40% of the total consumptive irrigation water use globally [*Siebert et al.*, 2010; *Wada et al.*, 2012]. The use of green and blue water by various crops has been estimated in global hydrologic models such as LPJmL [*Gerten et al.*, 2011] and H08 [*Hanasaki et al.*, 2010]. Yet never has it been assessed how much of an impact specific crop types have on groundwater resources of a specific aquifer system, usually because adequate agricultural and water use data are not available [*Wada et al*., 2010].

Our objective is therefore to identify which groundwater-irrigated crops contribute to aquifer stress using both global and local data sets, and assess the uncertainty of estimates of groundwater stress. To this end, we have developed a methodology that uses high-resolution agricultural and water use data and we demonstrate how this methodology can be applied to two aquifer systems. Although groundwater depletion is a global problem [*Aeschbach-Hertig and Gleeson*, 2012], significant depletion occurs locally in discrete aquifer systems. We therefore focus on two of the most stressed aquifer systems in the U.S. [*Gleeson et al*., 2012], where high-resolution agricultural and water use data are readily available: the Central Valley and the High Plains aquifer systems. The U.S. has indeed the second highest rate of groundwater consumption in the world [*Siebert et al*., 2010] and these two aquifer systems have the highest rate of groundwater abstraction in the U.S. [*Alley*, 2006]. The resulting groundwater depletion poses a threat to the agricultural economy of the U.S. since market value of agricultural products grown in the Central Valley and the High Plains, respectively, contributed up to 7% and 11.7% to the nation's $300 billion in agricultural revenue in 2007 [*Scanlon et al*., 2012]. To consider the within-aquifer spatial variability, the two aquifer systems were subdivided into their aquifers (e.g., Sacramento Valley, Tulare basin, San Joaquin basin, Eastside, and Delta for the Central Valley aquifer system) and those aquifers were in turn subdivided into the U.S. counties overlying them, enabling the use of county-scale reports of both crop areas and groundwater abstractions, which include a finer spatial variability compared to global data sets. Results have implications for water resource managers in the area but also extend beyond the U.S. borders through the export of commodities containing "virtual" groundwater.

2. Methodology

2.1. Theory

The groundwater footprint (GF) was first introduced in *Gleeson et al*. [2012] as the area required to sustain groundwater use and groundwater-dependent ecosystem services of a region of interest, such as an aquifer, watershed, or community. Since it is effectively an aquifer water balance, we clarify the definition as "the area required to sustain groundwater use and groundwater-dependent ecosystem services of an aquifer." Its mathematical definition is $GF=\frac{C}{R-E}\times A_{aq}$, where C, R, and E are, respectively, the area-averaged annual abstraction of groundwater, recharge rate including artificial recharge (from irrigation), and the groundwater contribution to environmental streamflow, all in units of L/T such as m/d [*Gleeson et al*., 2012]. A_{aq} (units of L^2 such as m^2) is the areal extent of an aquifer, where C, R, and E are defined. R represents the sum of long-term natural areal flux into the system and additional artificial recharge from irrigation. Recharge can be derived from global and local hydrologic models [*Döll*, 2009; *Faunt*, 2009; *van Beek et al*., 2011] as well as chloride and field data [*Scanlon et al*., 2012], although it could also be derived from geochemical tracer methods [*McMahon et al*., 2011]. Sustaining ecosystem services requires that a certain amount of groundwater (E) be allocated to surface water flow. E is assumed to be a fraction of R for an aquifer [*Gleeson et al*., 2012] even though environmental flow requirements are best determined by detailed hydroecological data and multidisciplinary expert consultation [*Poff et al*., 2009; *Richter et al*., 2012, 2003; *Smakhtin et al*., 2004]. This fraction can be calculated as the ratio of Q_{90} (the monthly streamflow exceeded 90% of the time, considered as the low flow), to Q_{avg}, the long-term average streamflow [*Gleeson et al*., 2012] although Q_{90} is not always a good representation of groundwater discharge. Aquifer stress is indicated by a ratio of groundwater footprint to aquifer area greater than 1 $\left(\frac{GF}{A_{aq}}\geq 1\right)$.

The notation section and equations below are as generic as possible so that they can be applied to other regions of the world, although some variables are defined based on the spatial resolution of data available in the study area. For example, the *co* subscript for county is meaningful in the U.S. but could be modified to a different jurisdictional name or physiographic region with a similar scale in other places. All variables are defined in the notation section and described in more detail below. We use the term abstraction to designate withdrawal and for clarity, we do not use the term consumption (the difference between abstractions and return flows).

Our methodology is depicted in Figure 1 for the case of corn in the Central Valley aquifer system. The mathematical definition of the groundwater footprint was in this study adapted to use available data.

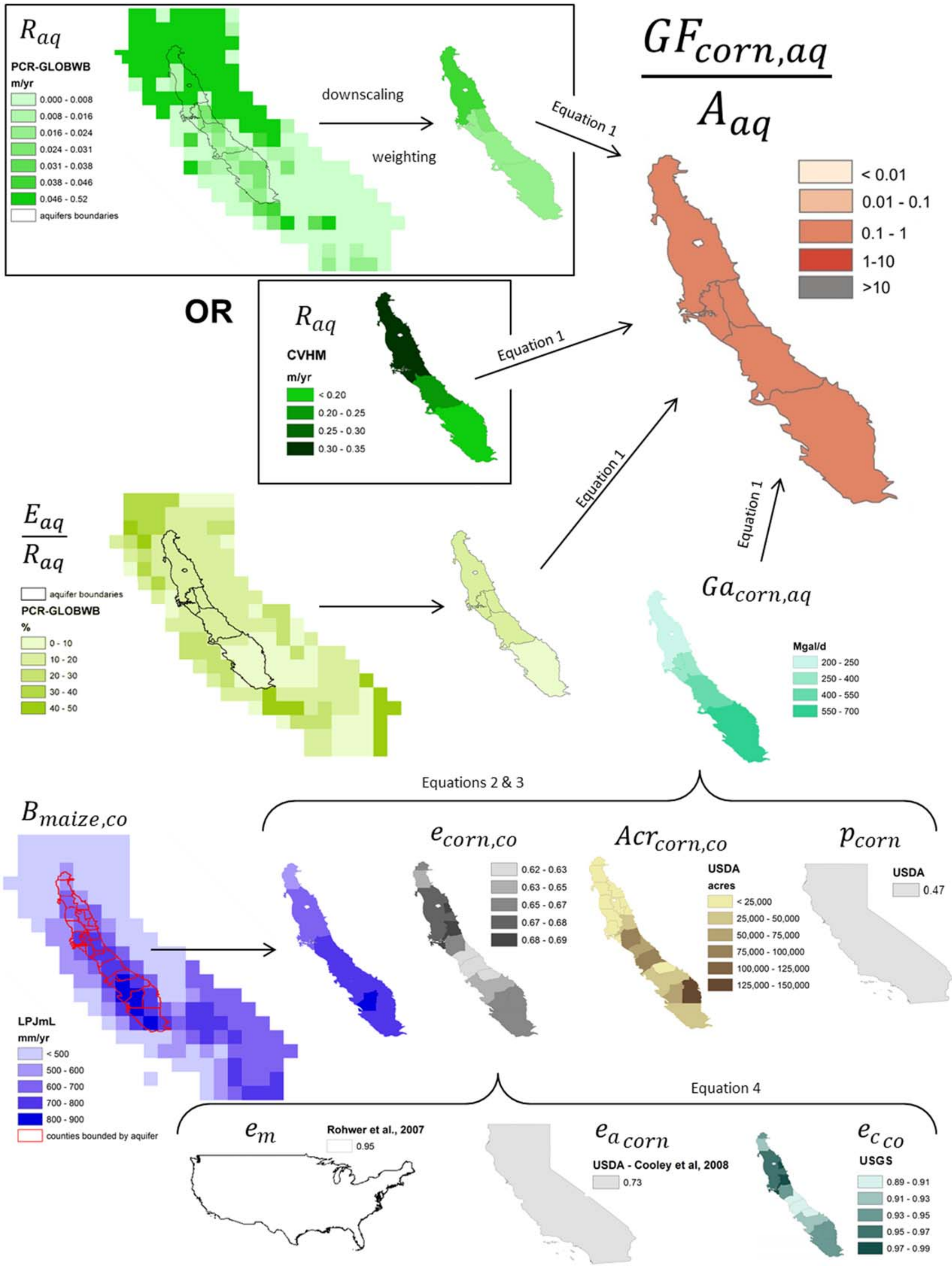

Figure 1. Flow chart of data sources and analysis to results for corn in the Central Valley aquifer system.

Groundwater abstraction as defined above (C) of a given crop type i (such as wheat or corn) is thus alternatively defined as $C_i = \frac{Ga_{i,aq}}{A_{aq}}$ in the groundwater footprint of a given crop type i of an aquifer (equation (1)). Since recharge, environmental flow requirements and hence groundwater footprint are defined at aquifer-scale, the groundwater abstraction of a given crop type i derived from a smaller scale (here, counties) was amalgamated at aquifer-scale (equation (2)). Crop groundwater abstraction of a given type i was first calculated at county-scale due to the availability of irrigated acreage and irrigation efficiency per crop type i at this scale (equation (3)). This also required crop type i's net blue water requirements to be calculated at county-scale (see section 2.2.2 and Figure 1):

$$GF_{i,aq} = \frac{Ga_{i,aq}}{R_{aq} - E_{aq}} \quad (1)$$

where the aquifer-scale groundwater abstraction is:

$$Ga_{i,aq} = \sum_{\{\forall co,\, co \cap aq \neq \varnothing\}} Ga_{i,co} \quad (2)$$

where the county-scale groundwater abstraction is:

$$Ga_{i,co} = \frac{B_{i,co}}{e_{i,co}} \times Acr_{i,co} \times p_i \quad (3)$$

where the total irrigation efficiency is:

$$e_{i,co} = e_{c_{co}} \times e_{ai} \times e_m \quad (4)$$

As defined in this study, total irrigation efficiency ($e_{i,co}$) and irrigated crop area ($Acr_{i,co}$) do not depend on the irrigation water type, that is to say groundwater or surface water. Therefore, equation (3) could equally be valid for surface water by substituting the areal proportion of crop area irrigated by groundwater by its surface water equivalent. This suggests that with different data this method could be adapted to surface water systems.

The net blue water requirement (B_i) is the areal flux of blue water needed for a crop to grow optimally, which implies that deficit irrigation and over irrigation are not considered in this methodology. Such practices could be taken into account by multiplying the net blue water requirement in equation (3) by a term depending on the crop type and the scale of data available. Furthermore, net blue water requirements do not capture water lost due to irrigation inefficiencies ($e_{i,co}$), which is comprised of three components: conveyance system efficiency ($e_{c_{co}}$), application system efficiency (e_{a_i}), and a management factor (e_m) (equation (4)), which are described in supporting information. Dividing B_i by $e_{i,co}$ takes into account return flows (that part of lost water that recharges blue water resources) so that the quantity $\frac{B_{i,co}}{e_{i,co}} \times Acr_{i,co}$ represents an abstraction.

The variable $Acr_{i,co}$ is the irrigated and planted area of a given crop type at county-scale. However, this quantity may not be readily available in data sets and might need to be represented by irrigated and harvested area instead, which can be less than the planted area (see section 2.2.1). The groundwater-irrigated and planted area is then derived using the areal proportion of irrigated crop area fed by groundwater (p_i).

Water that is applied for on-field practices (preirrigation, frost protection, application of chemicals, weed control, leaching salts from the root zone, etc.) can be locally important but is not included here since these are difficult to estimate and we assume it is likely that they do not represent a significant amount of groundwater abstraction. Also, gray water (the amount of water that was directly and indirectly polluted to produce the crops) is not included in our calculations since the groundwater footprint focuses on groundwater quantity and not groundwater quality [*Gleeson et al.*, 2012].

2.2. Data

2.2.1. Data Sources

Table 1 summarizes the hydrologic and agricultural data analyzed. We use long-term averages for recharge, environmental flow requirement, and net blue water requirement and the most recent data on water use efficiency and irrigated acreages, generally from the mid or late 2000s. The most recent available data were used which implies that not all the data have the same temporal resolution or coverage (Table 1). One set of efficiency data was last collected in the 1990s; we use these data assuming that conditions have not

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Table 1. Hydrologic and Agricultural Data

			$Ga_{i,co}$ Groundwater Abstraction						
						$e_{i,co}$ Total Irrigation Efficiency			
Term	R_{aq} Recharge	E_{aq} Environmental Flow Requirements	$B_{i,co}$ Net Blue Water Requirements	$Acr_{i,co}$ Irrigated and Harvested Crop Areas	p_i Areal Proportion of Irrigated Crop Area Irrigated by Groundwater	$e_{c_{co}}$ Conveyance System Efficiency	e_{a_i} Application System Efficiency	e_m Management Factor	Ga_{co} Total Groundwater Abstraction
Sources	CVHM model and measurements [*Faunt*, 2009; *Scanlon et al.*, 2012]	PCR-GLOBWB model [*Gleeson et al.*, 2012]	LPJmL model [*Gerten et al.*, 2011]	USDA census of agriculture [*NASS*, 2009]	USDA irrigation survey [*NASS*, 2008]	USGS water use survey [*Solley et al.*, 1998]	USDA irrigation survey [*NASS*, 2008] Method efficiency [*Cooley et al.*, 2008]	Irrigation efficiency estimates [*Rohwer et al.*, 2007]	USGS water use survey [*Kenny et al.*, 2009]
Spatial resolution	Aquifer	$0.5° \times 0.5°$	$0.5° \times 0.5°$	County	State	County	State	Nation	County
Crop-specific data	No	N.A.	Yes (Crop Functional Type)	Yes (individual crops)	Yes (individual crops)	No	Yes (individual crops)	No	No
Temporal range	1962–2003 and 1950–2007	1958–2000 average	1971–2000 average	2007	2008	1995	2007/2008	2007	2005
Original data unit	km^3/yr	m/yr	mm/yr	acres	dimensionless	dimensionless	dimensionless	dimensionless	Mgal/d

significantly changed. Long-term yearly averages run over about 30–40 years and do not include data after 2000 exclusive; we consider that those averages are reasonable (assuming a stationary climate) and represent a standard year. Data are derived from three scales: county (average size over U.S. is ~3000 km^2 with wide variations form East to West), state (average size over U.S. is ~200,000 km^2), and nation (~10,000,000 km^2). Areas of the High Plains and Central Valley aquifer systems were subdivided into three and five aquifers, respectively, based on detailed hydrogeological mapping [*Faunt*, 2009; *Weeks et al*., 1998].

Irrigation water type is assumed to be taken as blue water from surface or groundwater only. Desalination and wastewater reclamation (wastewater that has been treated for nonpotable reuse) for irrigation purposes are not considered in this study because they are likely not significant. Saline water sources constitute a negligible proportion of public supply sources in the U.S. [*Kenny et al*., 2009] and reclaimed wastewater is only used on 3.6% and 0.5% of irrigated land in, respectively, California and the states underlain by the High Plains aquifer system [*NASS*, 2008]. Recycling (reuse of surface or groundwater that has already been used to irrigate a crop on the farm) is also a practice that was not considered in this study for the same reasons; 8.8% and 1.3% of irrigated land in, respectively, California and the states underlain by the High Plains aquifer system use recycled water, but in unknown proportions of irrigated water [*NASS*, 2008].

The net blue water requirement (B_i) used in our study is averaged for 12 different crop functional types in the LPJmL model on a 0.5°-by-0.5° grid (i.e., ~50 km-by-50 km grid at the equator) over the period 1971–2000 [*Gerten et al*., 2011]. We assigned individual crop types from agricultural census data to each crop functional type (supporting information Table S1). Although horticultural operations (notably tomatoes, almonds, pistachios, or fruits) may be important in California and Texas [*Dickens et al*., 2011], they are not considered here since they are not analyzed as a crop functional type in the LPJmL model. Note that we used outputs from a global model to simulate B_i instead of crop coefficients used notably by the USGS [*Dickens et al*., 2011], because LPJmL dynamically calculates net blue water requirements rates on a daily basis using soil, precipitation, and temperature data sets [*Rost et al*., 2008], which is more spatially and temporally accurate (see supporting information for more details on LPJmL).

We used the different types of irrigation efficiencies as identified in *Rohwer et al*. [2007]. The conveyance system efficiency ($e_{c_{co}}$) was derived from USGS conveyance losses estimates [*Solley et al*., 1998]. Application system efficiency (e_{a_i}) was derived from a special tabulation of the USDA Farm and Ranch Irrigation Survey [*NASS*, 2008] and *Cooley et al*. [2008]. The management factor (e_m) for the U.S. is given in *Rohwer et al*. [2007] (see supporting information for more details).

The total groundwater abstraction for irrigation at county level Ga_{co} is also estimated by the USGS using various methods depending on states [*Kenny et al*., 2009], but is only reported as aggregates over all crops. This data set is compared as explained in section 2.2.2 to our own estimates, when summed over all the crop types considered. See section 3.1.1 for the results of this comparison and supporting information for more details on USGS data on groundwater abstraction for irrigation.

Only irrigated and harvested (in contrast to irrigated and planted) areas are reported precisely in the USDA Census of Agriculture [*NASS*, 2009]. Though failed crop areas are reported (0.7% of cropland in California and on average 1.2% of cropland in the states underlain by the High Plains aquifer system), they are aggregated for all crop types that failed and no indication is provided on the stage at which the crops failed, whereas beyond the crop type itself, such a stage also determines the extent of water used before crop failure. It is also likely that those areas that failed were more of the nonirrigated type since in case of droughts, for instance, irrigation can be increased on land equipped with irrigation systems to compensate for the lack of rainfall, which is not the case on rainfed cropland. USDA's National Agricultural Statistics Service (NASS) annually releases county-scale estimates on planted crop areas but does not distinguish irrigated and nonirrigated crop areas within it. The variable $Acr_{i,co}$ is therefore here the irrigated and harvested area of crop type *i* as reported in the USDA Census of Agriculture, though it would have been preferable to use the irrigated and planted area had it been available.

The areal proportion of crop area irrigated by groundwater (p_i) was derived at state level and per crop type from the USDA Farm and Ranch Irrigation Survey [*NASS*, 2008]. The variable was calculated as the ratio between the harvested acres of a given crop type irrigated by groundwater from wells ($Acr_{groundwater}$), augmented by 5% of the harvested acres irrigated by water from off-farms suppliers ($Acr_{water\ from\ off\ farm\ suppliers}$), and the sum of harvested acres for the same crop type irrigated with groundwater from wells, on-farm surface water ($Acr_{surface\ water}$), and water from off-farm suppliers (equation (5)). The latter is indeed considered to be composed of only ~5% of groundwater nationally [*USDA*, 1997]. We moreover disregarded the possibility that groundwater may be more resorted to with higher or lower efficiency irrigation systems, depending on the price of groundwater compared to that of surface water.

$$p = \frac{Acr_{groundwater} + 0.05 \times Acr_{water\ from\ off\ farm\ suppliers}}{Acr_{groundwater} + Acr_{surface\ water} + Acr_{water\ from\ off\ farm\ suppliers}} \tag{5}$$

Multicropping was implicitly considered as the USDA Census of Agriculture includes acres subject to multicropping in the total irrigated area of each crop sown on the same land at different times. However, we only implicitly consider multicropping because first, LPJmL does not account for multicropping (net blue water requirements are for a single cropping cycle) and second, the USDA generally provides no indication on the period of the year when the crops on multicropped land were grown.

Recharge (R_{aq}) was derived from different data sets. The global hydrologic model PCR-GLOBWB was used for both the Central Valley and the High Plains and local data sets were also used from the Central Valley Hydrological Model (CVHM) [*Faunt*, 2009; *Scanlon et al.*, 2012] and, for the High Plains, from groundwater chloride and field data [*Scanlon et al.*, 2012]. Values from PCR-GLOBWB constitute averages over 1958–2000 on a 0.5°-by-0.5° grid [*Wada et al.*, 2010]. Recharge is calculated in the model as the net positive downward flux from the second to the third soil layers. The CVHM is a detailed three-dimensional MODFLOW-based model that uses a farm mass balance to estimate evaporation, transpiration, runoff, and deep percolation to groundwater in the Central Valley [*Faunt*, 2009]. Environmental flow requirements (E_{aq}) are defined as a fraction of recharge from the PCR-GLOBWB model and are calculated as outlined above in theory (see supporting information for a detailed description of the PCR-GLOBWB model).

2.2.2. Data Handling and Comparison

Spatial data were analyzed with ESRI's ArcMap 10.0 suite. Rates (R_{aq}, E_{aq}, and $B_{i,co}$) that were calculated on a 0.5°-by-0.5° grid were first downscaled to a 0.01°-by-0.01° grid (1 km-by-1 km grid at the equator; supporting information Figure S1a). This resolution was chosen for the boundaries of the smallest counties in mainland U.S., which are ~60 km^2, to be reasonably approximated. The 0.01° raster rates were then attributed to individual aquifers (R_{aq}, E_{aq}) or counties ($B_{i,co}$) (supporting information Figure S1b) and weighted. The weighting factor is equal to the 0.01° raster area divided by the sum of the 0.01° raster areas within the county or aquifer (supporting information Figure S1c). The weighted 0.01° raster rates for each aquifer or county were finally summed over the aquifer or county (supporting information Figure S1d). When part of a county was situated outside of the considered aquifer system boundaries, the values of these rates were derived for the intersection between the county and the aquifer system areas.

If part of a county was situated outside of an aquifer area, possible modifications to county-scale reported data such as total groundwater abstraction (Ga_{co}) and irrigated and harvested crop area ($Acr_{i,co}$) were accounted for on a case-by-case basis. As detailed in supporting information, we assigned without modification county-scale reported data to the intersection between county and aquifer areas in the Central Valley, while we adopted a weighting-factor approach for those county-scale reported data in the High Plains.

The primary focus of this study being the impact of different crop types on groundwater stress, we cannot use USGS estimates of groundwater abstraction for irrigation directly to calculate crop-specific groundwater footprints, as they amalgamate all crop types without distinction. However, we can use USGS estimates to derive the groundwater footprint of agriculture (horticulture excluded; supporting information Table S4) and compare them to ours through equation (6), which quantifies the total groundwater abstraction for crop irrigation at county-scale:

$$Ga_{co} = \sum_i \frac{B_{i,co}}{e_{i,co}} \times Acr_{i,co} \times p_i \tag{6}$$

We performed paired statistical tests to assess differences between the two estimates (see supporting information for more details on statistical tests performed). We also compared USGS estimates of both groundwater and surface water abstraction to our estimates of blue water abstraction for irrigation at county-scale (equation (6) without the term p_i) in order to observe if a significant difference between the two sets of groundwater abstraction estimates translates into a significant difference between the two sets of blue water abstraction estimates in a given area.

2.3. Uncertainty Analysis

The uncertainty of ratios of groundwater footprint to aquifer area was calculated by considering the uncertainty of each parameter in equations (1–4), assuming the uncertainty sources are independent. Since relative uncertainties sum, the relative uncertainty of the ratio of groundwater footprint of a given crop type to aquifer area is:

$$\frac{\Delta\left(\frac{GF_{i,aq}}{A_{aq}}\right)}{\frac{GF_{i,aq}}{A_{aq}}}=\frac{\Delta Ga_{i,aq}}{Ga_{i,aq}}+\frac{\Delta R_{aq}}{R_{aq}}+\frac{\Delta\frac{E_{aq}}{R_{aq}}}{1-\frac{E_{aq}}{R_{aq}}} \tag{7}$$

where Δ denotes the absolute uncertainty of the term that follows directly. The relative uncertainty of groundwater abstraction for irrigation of a given crop type is:

$$\frac{\Delta Ga_{i,aq}}{Ga_{i,aq}}=\frac{\sum_{\{\forall co,\, co\cap aq\neq\emptyset\}} Ga_{i,co}\times\left[\frac{\Delta B_{i,co}}{B_{i,co}}+\frac{\Delta e_{i,co}}{e_{i,co}}+\frac{\Delta Acr_{i,co}}{Acr_{i,co}}+\frac{\Delta p_i}{p_i}\right]}{Ga_{i,aq}} \tag{8}$$

We calculated the relative uncertainty of net blue water requirements $\frac{\Delta B_{i,co}}{B_{i,co}}$ at aquifer-scale since reporting it at county-scale would not necessarily result in added accuracy in estimating the total uncertainty, as the other relative uncertainties are reported at significantly larger scales (supporting information Table S2) and B_i is originally derived at a 0.5°-by-0.5° raster spatial resolution. This simplifies equation (8) as follows:

$$\frac{\Delta Ga_{i,aq}}{Ga_{i,aq}}=\frac{\Delta B_{i,co}}{B_{i,co}}+\frac{\Delta e_{i,co}}{e_{i,co}}+\frac{\Delta Acr_{i,co}}{Acr_{i,co}}+\frac{\Delta p_i}{p_i} \tag{9}$$

The uncertainty of net blue water requirements $\frac{\Delta B_{i,co}}{B_{i,co}}$ is calculated at aquifer-scale following the same analysis performed to obtain net blue water requirement (supporting information Figure S1) and represents the relative difference between two different outputs of the LPJmL model using two different input precipitation data sets. The first precipitation data set is GPCC v.5 (full reanalysis) which is considered as the reference due to the efforts put into checking the quality of raw station data; the second is CRU TS 3.10 [*Harris et al*., 2013; *Rudolf et al*., 2010].

The uncertainty of irrigation efficiency at aquifer-scale $\frac{\Delta e_{i,co}}{e_{i,co}}$ is the sum of relative uncertainties on conveyance loss efficiencies, irrigation application efficiencies, and management factor at aquifer-scale. First, the uncertainty of conveyance loss efficiency can be high but conveyance losses are only significant for irrigation water from surface water bodies, and the conveyance efficiencies reported in *Solley et al*. [1998] are likely overestimated for most counties (generally between 0.9 and 1.0, except for counties in Colorado, Wyoming and New Mexico—states having few counties underlain by the High Plains aquifer system). We therefore decided that these values of conveyance efficiencies accurately describe the low conveyance losses associated with groundwater abstraction for irrigation and consequently assigned a ±5% uncertainty of conveyance efficiency for all states. Second, the uncertainty of irrigation application efficiency was calculated for each crop type at state scale, based on data summarized in supporting information Table S3. Each state value was assigned to the counties both within that state and the aquifer considered and the aquifer value was then calculated as the average over all counties within it. Third, we consider the uncertainty of the management factor to be zero because it is likely implicitly included in the uncertainty of the application techniques (supporting information Table S3), as it is difficult to differentiate the uncertainty that is due to the technique itself and to the "management" of the equipment.

The uncertainty of the harvested and irrigated acreage $\frac{\Delta Acr_{i,co}}{Acr_{i,co}}$ is available at national scale and is assumed to be the same at aquifer-scale. It is measured as the relative root mean squared error on reported acres of land in farms and equals 0.25% [*NASS*, 2009].

Table 2. Ratios of Groundwater Abstraction to Aquifer Area for Different Data Combinations[a]

	Abstraction: This Paper Recharge: *Scanlon et al.* [2012] and *Faunt et al.* [2009]	Abstraction: USGS Recharge: *Scanlon et al.* [2012] and *Faunt et al.* [2009][b]	Abstraction: This Paper Recharge: PCR-GLOBWB	Abstraction: USGS Recharge: PCR-GLOBWB[a]	*Gleeson and Wada* [2013]
Sacramento	0.3 ± 0.2	0.6	2.2 ± 1.3	4.2	3.3 ± 2.5
Eastside	1.7 ± 1.0	0.5	5.2 ± 3.1	6.4	7.2 ± 3.2
Delta	1.3 ± 0.8	0.5	7.5 ± 4.5	9.3	11.2 ± 11.2
San Joaquin	1.5 ± 0.9	0.8	13.4 ± 8.1	12.2	9.0 ± 2.0
Tulare	0.9 ± 0.5	1.1	9.9 ± 5.5	13.5	14.4 ± 6.5
Northern High Plains	5.2 ± 2.3	2.9	21.0 ± 9.4	12.1	4.3 ± 1.5
Central High Plains	11.2 ± 5.1	11.2	12.1 ± 5.6	13.6	8.2 ± 5.7
Southern High Plains	15.4 ± 8.3	9.7	12.2 ± 6.6	8.7	19.1 ± 19.8

[a]The first column is considered the most accurate and the corresponding data combination is that retained for discussion on crop-specific groundwater footprints.
[b]The values in the corresponding columns do not display uncertainty ranges because the USGS does not provide any quantitative measure of uncertainty and estimates encompass derivation methods of variable accuracy, depending on the state.

The uncertainty of acreages irrigated by any water source ($Acr_{any\ irrigation\ water\ source}$) is the same and is measured as the relative standard error of irrigated acres of cropland harvested [*NASS*, 2008], which is available at state scale (supporting information Table S2). Using equation (5), the uncertainty of the proportion of irrigated acreage being irrigated by groundwater is $\frac{\Delta p_i}{p_i} = 2 \times \frac{\Delta Acr_{any\ irrigation\ water\ source}}{Acr_{any\ irrigation\ water\ source}}$ and is calculated at aquifer-scale using an average over the number of counties that were assigned the $\frac{\Delta p_i}{p_i}$ of the state to which they belong.

The uncertainty of recharge is calculated at aquifer-scale following the same analysis performed to obtain net blue water requirement (supporting information Figure S1) and is estimated by comparing PCR-GLOBWB simulated runoff fields to station discharge from the Global Runoff Data Centre (http://www.bafg.de/GRDC) and also by comparing PCR-GLOBWB simulated recharge to that from WaterGAP [*Döll and Fiedler*, 2008]. A Monte-Carlo simulation is then performed generating 100 equiprobable realizations of groundwater recharge and the standard deviation is eventually calculated. We refer to *Wada et al*. [2010] for the detailed methods. Other recharge data sets (CVHM, chloride, and field data) do not have any uncertainty provided; we therefore assume they have the same relative uncertainty as that calculated for PCR-GLOBWB.

The uncertainty of environmental flow requirements, measured as a fraction of recharge, was not included since we consider environmental flow requirements as being primarily a management decision at state to nation scales.

3. Results and Discussion

We first compare the different results obtained with various combinations of data sets to illustrate the impact of input data on results. Then we examine the uncertainty of the results and the contribution of all input data to this uncertainty. Finally, we assess the results and their implications before discussing the applicability of the methodology to other areas.

3.1. Impact of Different Data Sets

As groundwater footprint to aquifer area ratios depend on groundwater abstraction and recharge, we compared two different data sets for each of them, as listed in Table 2.

3.1.1. Abstraction Data Sets

In the High Plains, our estimates of both groundwater and blue water abstraction are higher but not significantly different from the USGS' at a 95% confidence. For groundwater abstraction, the abstraction-weighted relative difference to USGS estimates over all counties is −50% and for blue water abstraction, −58%. In the Central Valley, the difference between USGS groundwater abstraction estimates and ours is not significant either (abstraction-weighted relative difference to USGS estimates of 23%) though in the case of blue water abstraction estimates, USGS' are significantly higher (abstraction-weighted relative difference to USGS estimates of 37%).

Differences between the two data sets arise from many different factors. For instance, we use detailed high-resolution reported data in conjunction with modeled data from larger scales, which we downscaled to county level. Some crop functional types do not suit well certain specific crop types, either because some individual crops had to be assigned the closest net blue water requirement we could find (for instance,

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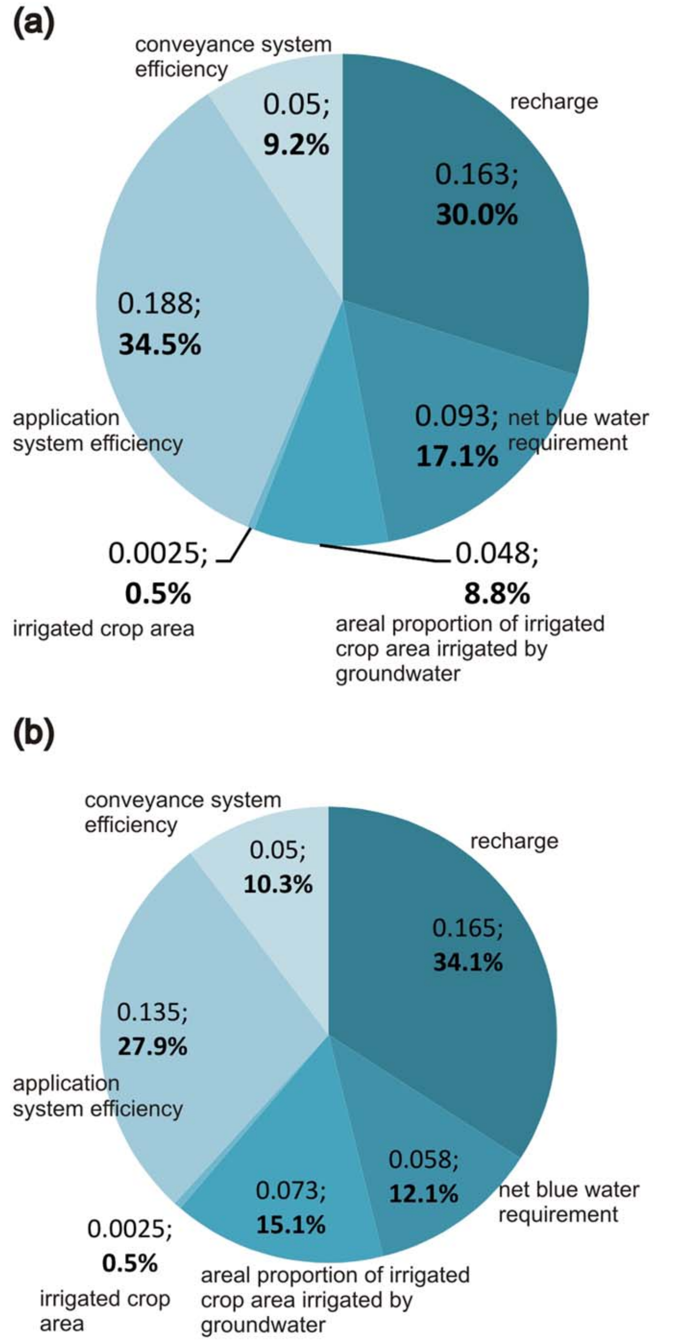

Figure 2. Contribution of parameter uncertainty to total relative uncertainty for (a) the Central Valley and (b) High Plains aquifer systems. The first value indicates the actual value of the relative uncertainty of the parameter in the aquifer system and the second value (%, in bold) indicates the relative contribution of this uncertainty to the total relative uncertainty in the aquifer system.

cotton has the net blue water requirement of the pasture crop functional type) or because some crop types are inherently difficult to model due to numerous varieties and ways of cultivation (supporting information Table S1). Note that wheat, maize (i.e., corn), and rapeseed are the best validated crop functional types in LPJmL. To reduce the sources of errors, the global models used in this study could be run with higher resolution input data and other global models such as H08 [*Hanasaki et al.*, 2010] could also be used (cotton is, for instance, explicitly modeled in the latter). The USGS estimation methods are poorly documented and vary greatly from state to state, thus not providing consistent accuracy between states [*Dickens et al.*, 2011].

The temporal resolution between the two sets of estimates is also not the same. This bears importance when considering that there are wide interannual variations in terms of droughts, notably in California, where severe droughts occurred between 2007 and 2009 [*Famiglietti et al.*, 2011; *Jones and Nguyen*, 2010]. It may therefore be likely that the harvested and irrigated acreage data retrieved in 2007 were lower that year compared to what it was in the years preceding the 2005 USGS estimation of groundwater abstraction, as shown by the comparison between the 2007 and 2002 acreage data [*NASS*, 2009].

Since each state has its own methodology to estimate groundwater and blue water abstractions, we also compare our estimates to USGS' for each of those three states with a sufficient number of pair differences to derive statistically robust conclusions (Kansas, Nebraska, and Texas). The USGS estimates were not found to be significantly different from ours, for groundwater abstraction in Texas (−24%) and Nebraska (3%, one outlier county removed) and for blue water abstraction in Nebraska (6%, one outlier county removed) and Kansas (−38%). USGS abstraction estimates of groundwater are only significantly lower than ours in Kansas (−38%) and USGS abstraction estimates of blue water are only significantly higher than ours in Texas (30%).

In their documentation of methods of USGS irrigation data, *Dickens et al*. [2011] compare USGS blue water abstraction estimates to estimates from the Indirect Irrigation Withdrawal Estimation Method (IIWEM) in a few states. IIWEM blue water abstraction estimates were significantly higher in California (16%) and in Texas (124%) while they were not significantly different in New Mexico and Wyoming. The good statistical correlation suggests our estimates of groundwater abstraction per crop type are reasonable; we therefore use them to derive results discussed in the subsequent analysis.

3.1.2. Recharge Data Sets

Groundwater recharge is generally more difficult to obtain than groundwater abstraction and is subject to high uncertainty [*Gleeson and Wada*, 2013]. We compared in the High Plains PCR-GLOBWB estimates to estimates based on chloride and field data [*Scanlon et al*., 2012]. The PCR-GLOBWB recharge rate in the Northern High Plains (9.5 $\pm$ 1.6 mm/yr) is significantly lower than the corresponding long-term annual and spatial mean recharge rate as reported in *Scanlon et al*. [2012] (39.0 mm/yr, no uncertainty range). PCR-GLOBWB is known to have low recharge in the Northern High Plains, a phenomenon that is not captured in the parameter uncertainty analysis since the deviation from 9.5 mm/yr is only 1.6 mm/yr, leading to ratios being overestimated in the Northern High Plains with the PCR-GLOBWB recharge value. Nevertheless, in both the Central and Southern High Plains, our recharge estimates are consistent with *Scanlon et al*. [2012]: PCR-GLOBWB models 8.3 $\pm$ 1.3 and 11.7 $\pm$ 2.0 mm/yr in, respectively, the Central and Southern High Plains while *Scanlon et al*. [2012] finds 10.0 and 10.3 mm/yr, respectively, thus suggesting the model estimates in this region are accurate. Different geochemical tracer methods summarized in *McMahon et al*. [2011] give between 20 and 1200 mm/yr in the Northern High Plains and 7 mm/yr in the Central High Plains.

The comparison of PCR-GLOBWB recharge estimates to CVHM [*Faunt*, 2009] in the Central Valley highlights significant discrepancies. The CVHM finds between 8 and 15 times higher recharge than PCR-GLOBWB depending on the aquifer (Sacramento: 344 mm/yr versus 45.8 $\pm$ 7.6 mm/yr or San Joaquin: 241 mm/yr versus 16.1 $\pm$ 2.7 mm/yr). Both models include recharge from precipitation and irrigation. But while the CVHM is a local highly parameterized model, PCR-GLOBWB is a global 0.5° grid-resolution model. Recharge from large-scale surface water diversions like the Central Valley Project or California State Water Project is therefore only taken into account in the local model. As a means of comparison, different geochemical tracer methods yield modern recharge rates between 420 and 580 mm/yr over the entire Central Valley [*McMahon et al*., 2011].

3.2. Total Groundwater Stress and Uncertainty

The uncertainty of groundwater footprint to aquifer area ratios, we derive is obtained by propagating the uncertainty of different parameters in equation (3). This method allows assessing which of the parameters account for the highest relative uncertainty (Figure 2), although this also depends on how that uncertainty was calculated. For instance, this uncertainty analysis does not capture the uncertainty due to the assignment of USDA-listed crop types to crop functional types, which may result in actual uncertainty of net blue water requirement being higher for certain crop types, notably cotton (supporting information Table S1). Note that consistent with previous studies, we made best estimates and uncertainty precise up to one decimal place though it sometimes leads to uncertainty having two significant digits (Table 2). Finally, the uncertainty of the groundwater footprint can be visualized by comparing the areal extent of the best estimate with that of the lower and upper limits of the footprint of all aquifers in both the Central Valley (Figure 3a) and the High Plains (Figure 3b).

3.2.1. Contribution of Parameter Uncertainty to Total Uncertainty

Figure 2 was drawn by first averaging crop-specific quantities over all crops in each aquifer system and then by taking the area-weighted average of each parameter uncertainty over all aquifers in each aquifer system. This enables having one diagram for each aquifer system, which is justified by aquifer systems having similar parameter uncertainty values in a given aquifer system.

The contribution of each parameter uncertainty to total relative uncertainty is similar between the Central Valley and the High Plains (Figure 2) although slight differences can be noted. Both recharge and irrigation application efficiency yield the highest contribution to total relative uncertainty in both aquifer systems; however, the biggest uncertainty contributor is irrigation application efficiency in the Central Valley (34.5%) while it is recharge in the High Plains (34.1%). While the actual value of the relative uncertainty of recharge is very close in both the Central Valley and the High Plains (0.163 and 0.165, respectively), this difference in first contributors is due to the actual value of irrigation application efficiency being higher in the Central

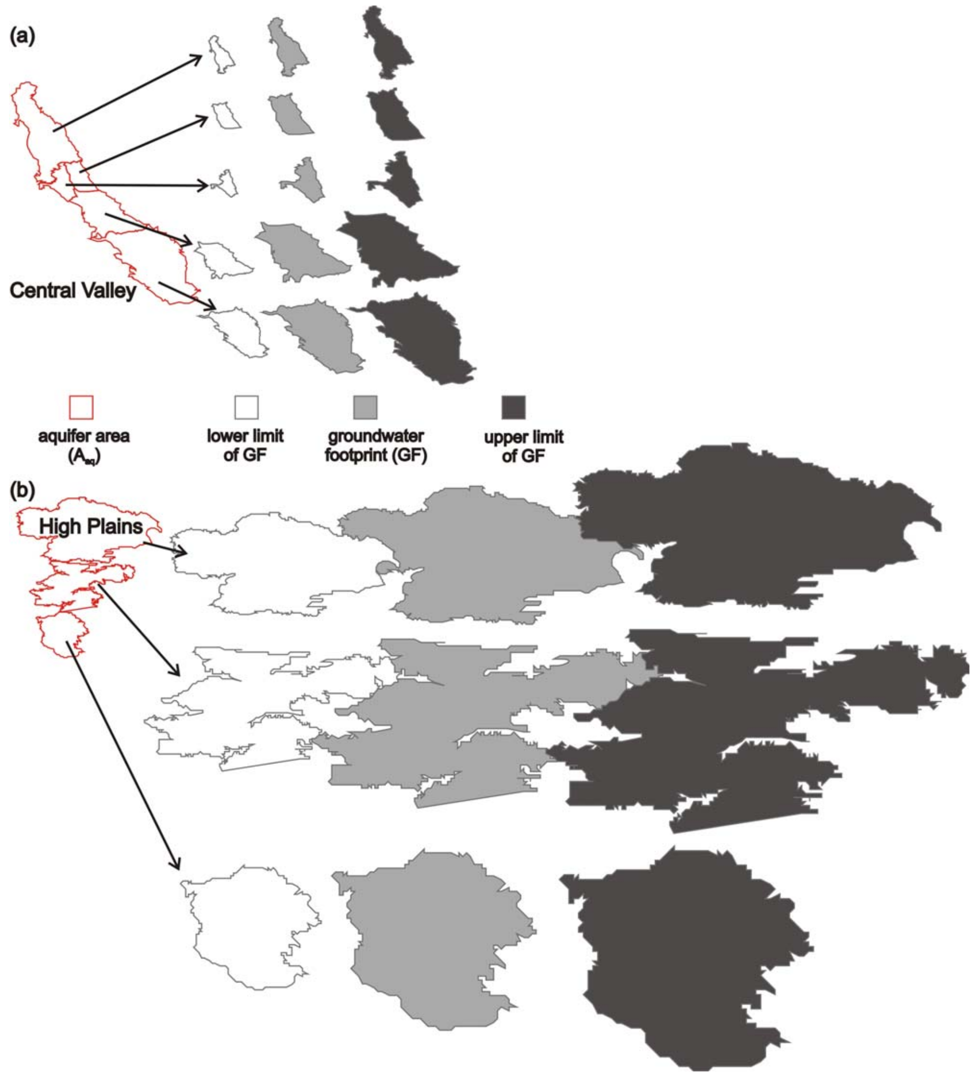

Figure 3. Visualization of how uncertainty impacts the groundwater footprint for (a) the Central Valley and (b) the High Plains aquifer systems. All maps shown at the same scale with the groundwater footprint in gray, -1σ lower limit in white and $+1\sigma$ limit in black.

Valley (0.188) than in the High Plains (0.135). This originates from California having a significantly lower irrigation application efficiency for important crops (notably corn, hay, and pasture) than most states overlapping the High Plains (supporting information Table S5); though normally the value of a best estimate is not indicative of its uncertainty, the most inefficient irrigation methods (surface ditch/furrow, wild flooding, etc.) are often associated with bigger uncertainty ranges (supporting information Table S3).

The contribution of uncertainty of net blue water requirements is higher in the Central Valley (17.1%) than in the High Plains (12.1%), as is the actual value of the relative uncertainty of net blue water requirements (0.093 in the Central Valley versus 0.058 in the High Plains). This is explained by a bigger discrepancy between the two precipitation data sets used to derive the uncertainty of net blue water requirement in the Central Valley than in the High Plains, most likely because California experiences more extreme spatial [*Scanlon et al*., 2012] and temporal [*NOAA*, 2014] patterns of precipitation than in the High Plains.

The inverse applies for the proportion of irrigated acreage irrigated by groundwater, whose relative uncertainty contributes this time more in the High Plains (15.1%) than in the Central Valley (8.8%) to the total relative uncertainty. The actual value of the relative uncertainty of the irrigated acreage irrigated by groundwater is also higher in the High Plains (0.073) than in the Central Valley (0.048).

3.2.2. Patterns of Total Groundwater Stress

Figures 4p and 5t present the ratios of the total groundwater footprint to aquifer area for the Central Valley and High Plains aquifer systems, respectively, and use the combination of abstraction data from this study and recharge data from *Scanlon et al*. [2012]. The northern most aquifer in the Central Valley, underlying the Sacramento Valley, has a lower ratio of total groundwater footprint to aquifer area (0.3 ± 0.2) than the remainder of the aquifers (Figure 4p); overlapping uncertainty ranges of ratios in the Eastside, Delta, San Joaquin, and Tulare aquifers make it impossible to further distinguish a finer stress pattern in the Central Valley (Table 2). The pattern identified in Figure 4p agrees though with the fact that 80% of groundwater depletion in the river basin containing the Central Valley aquifer system occurred in the south part, containing the Delta, Eastside, San Joaquin, and Tulare aquifers [*Famiglietti et al*., 2011]. Note that the Delta and Eastside aquifers have the size of one to two 0.5° rasters (Figure 1), which makes their ratios more susceptible to spatial errors or bias in the models used in this study to derive environmental flow requirement (PCR-GLOBWB) and net blue water requirement (LPJmL), indicating the data resolution may be too coarse for these areas. This source of error is not taken into account in the uncertainty analysis carried out in this study.

In the Central Valley, the large discrepancy in ratios between different data combinations and previous estimates (Table 2) is mostly due to the difference in recharge data sets discussed earlier. Predevelopment recharge in the Central Valley (48.2 mm/yr, before 1962) [*Faunt*, 2009; *Scanlon et al*., 2012], i.e., before the onset of irrigation and the advent of large-scale surface water diversions in California, is close to PCR-GLOBWB's recharge estimates (from 16.1 mm/yr in the San Joaquin aquifer to 45.8 mm/yr in the Sacramento aquifer), suggesting that surface water diversions could provide most of the recharge. Note however the return flow is generally of lesser quality than original groundwater [*McMahon et al*., 2008]. Besides, this may displace resource overexploitation from unsustainable groundwater pumpage (i.e., without artificial recharge from surface water diversions) to surface water capture endangering sensitive species [*Yoshiyama et al*., 1998, 2000]. The possibility of surface water not being diverted in 2014 due to extreme droughts may also limit the amount of aquifer recharge but also increase groundwater abstraction, a feedback that might possibly increase groundwater stress in the Central Valley.

Deriving a clear stress pattern in the High Plains is made difficult due to overlapping uncertainty ranges of the ratios of all three aquifers there. However, the Northern High Plains aquifer may have a lower ratio than the more southern ones (Table 2), which would match depletion gradients and cumulative change in groundwater storage identified by *Scanlon et al*. [2012] in the High Plains.

While the High Plains aquifer system is stressed, the Central Valley might not be stressed given the uncertainty calculated (supporting information Table S2). This highlights a crucial difference between the notions of stress and depletion: while the Central Valley is experiencing significant groundwater depletion, this is a long-term trend that does not necessarily result in the aquifer system being stressed continuously. *Scanlon et al*. [2012] indeed report that the cumulative change in groundwater storage in the Central Valley is non-monotonic (stress due to droughts alternating with partial replenishment) despite an overall decline trend (depletion) driven by the Tulare aquifer. As already pointed out, our study uses climate-dependent parameters that are averages over long temporal ranges (Table 1) and the use of recent acreage data is intended to show stress conditions in a given standard recent or near future year.

Discrepancies in ratios between previous estimates and ours may to a lesser extent be due to our study taking into account groundwater abstraction for crop irrigation—the focus of this study—while *Gleeson and Wada* [2013] also consider other water use categories (public supply, industrial, irrigation, mining, etc.). In California, 78% of groundwater withdrawn is used for irrigation of crops and the proportion is 73% on average in the states underlain by the High Plains. Besides, estimates from *Gleeson and Wada* [2013] presented in Table 2 are calculated from two different abstraction data sets (notably USGS data) and four recharge data sets (of which only PCR-GLOBWB data estimate artificial recharge from irrigation however).

Horticultural operations are not included in our estimates of groundwater abstraction for irrigation though they may contribute significantly to groundwater demand in California (particularly tomatoes, almonds, pistachios, or fruits) and Texas [*Dickens et al*., 2011] notably because some horticultural species have high net water requirements. In such a likely case, horticulture would stress even more the whole Central Valley aquifer system and the Southern High Plains aquifer.

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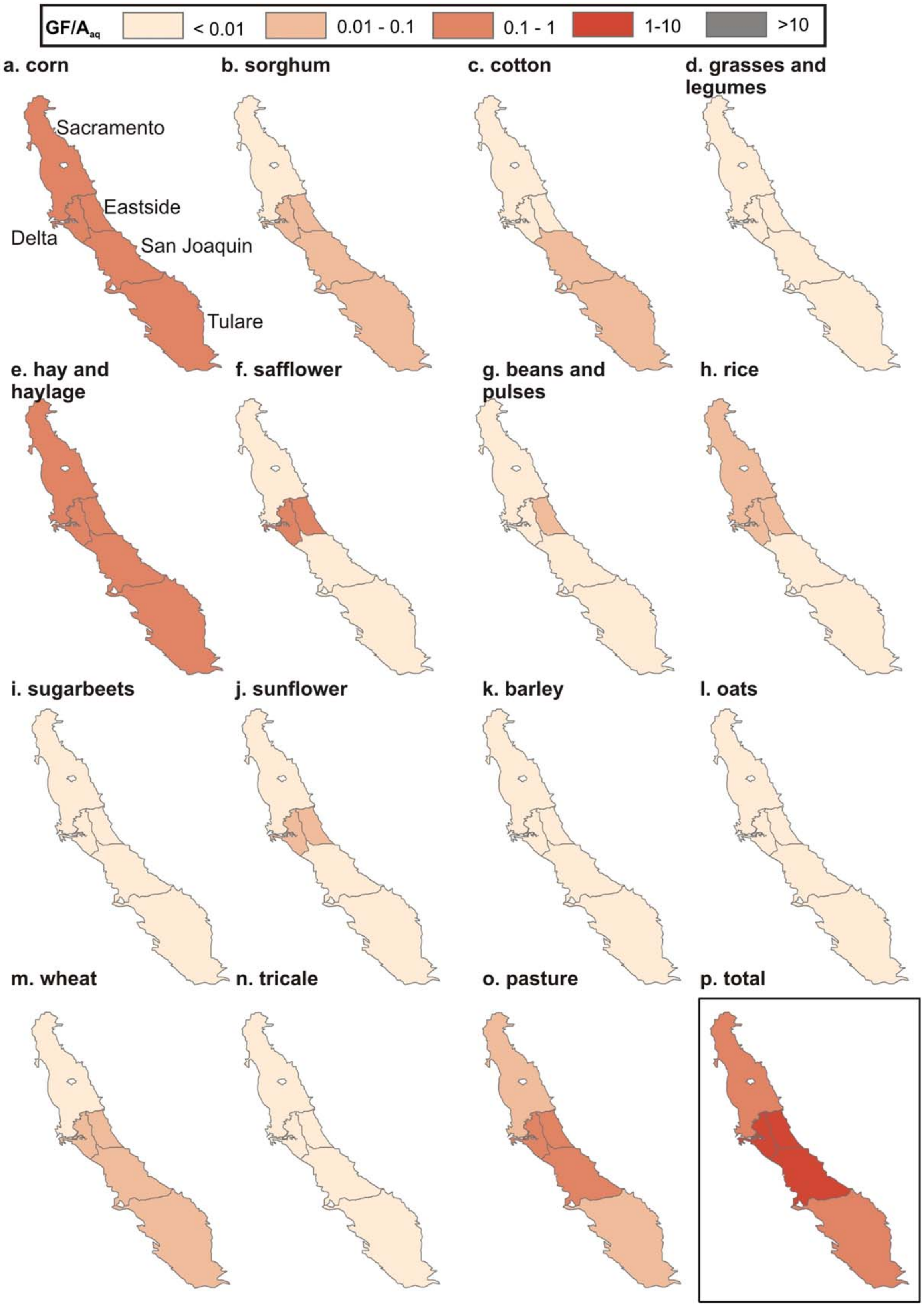

Figure 4. Ratio of groundwater footprint to aquifer area for crop types in the Central Valley aquifer system.

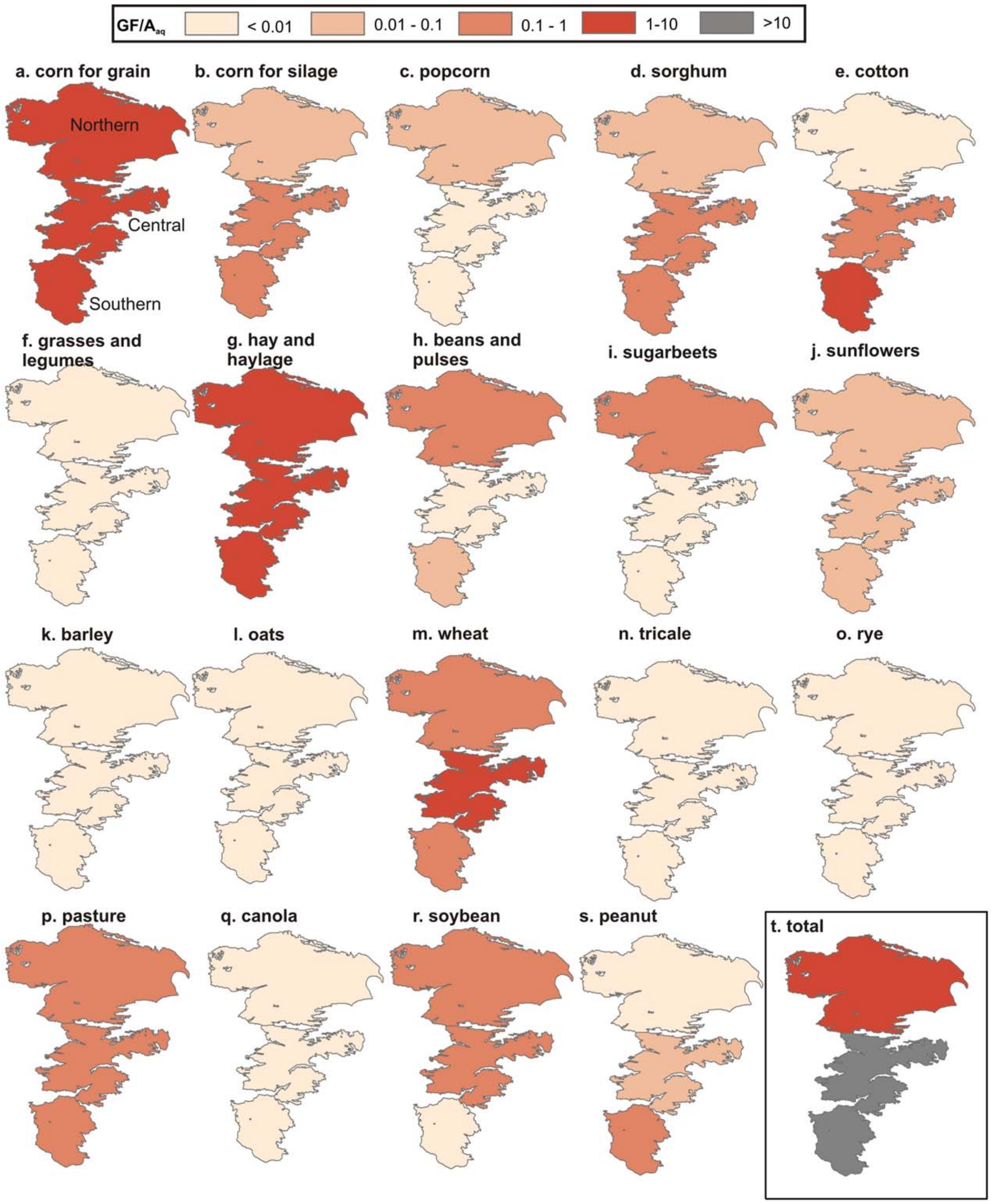

Figure 5. Ratio of groundwater footprint to aquifer area for crop types in the High Plains aquifer system.

We did not account for seasonal groundwater use variations because the input data sets we used do not provide indications on cropping seasons as well as their associated acreage and associated net blue water requirement for each crop type. Nevertheless, irrigation exhibits a large seasonal water demand depending on the cropping seasons and seasonal variations of crop-specific water demand, but also groundwater abstraction, recharge, and environmental flow requirements, which could result in highly useful groundwater footprint temporal patterns.

3.3. Aquifer-Scale Groundwater Stress for Individual Crops

Figures 4 and 5 also present the ratios of groundwater footprint to aquifer area for crop types in the Central Valley and High Plains aquifer systems. Note that some crop types do not grow (or have negligible acreage) over one of the two aquifer systems. For example, rice is grown in the Central Valley but not in the High Plains whereas soybean is grown in the High Plains and not in the Central Valley. An additional difference is that corn is divided in the High Plains into corn for grain, corn for silage and popcorn, which allows us to assess the differences between types of corn in this region of high density of corn-fed livestock farming.

Groundwater footprint to aquifer area ratios exhibits significant spatial variations, both for a same crop type between the two aquifer systems, and between different crop types in a given aquifer system (Figures 4 and 5). When comparing crops within a given aquifer, differences in ratios are due to net blue water requirement, acreage, irrigation application efficiency, and proportion of irrigated acreage irrigated by groundwater. Note that recharge estimates are not dependent on crop in a given aquifer. Even though total irrigation efficiency is crop dependent, it has in fact limited influence on ratios in this study since the total irrigation efficiency does not vary considerably between crop types (supporting information Table S5).

In the Central Valley, the highest values of the ratio in the northern most Sacramento Valley are due to hay and haylage, rice as well as pasture (Figures 4e, 4h, and 4o) though no individual crop stresses the aquifer $\left(\frac{GFi,aq}{Aaq} < 1\right)$. In the central part of the aquifer system (San Joaquin, Eastside, and Delta), hay and haylage, corn, and pasture account for high values of the ratio (Figures 4e, 4a, and 4o); only do hay and haylage possibly stress those central aquifers however (Eastside: 0.7 ± 0.5; Delta: 0.6 ± 0.4; San Joaquin: 0.6 ± 0.4). Cotton is also prominent in the San Joaquin and Tulare aquifers (Figure 4c) but leads to no individual stress. Besides, hay and haylage, and corn have the most important but nonstressing ratios in the Tulare aquifer (Figures 4e and 4a).

The Northern High Plains aquifer is stressed by corn for grain (Figure 5a), and likely by hay and haylage (Figure 5g, "likely" indicating the lower bound of the uncertainty range does not lead to stress unlike the upper), while soybean and pasture are also amongst higher ratios, though nonstressing (Figures 5s and 5p). The Central High Plains is stressed by corn for grain and wheat (Figures 5a and 5m), and likely by hay and haylage (Figure 5g). Finally, cotton has a stressing ratios in the Southern High Plains aquifer (Figure 5e), and likely hay and haylage, as well as corn for grain (Figures 5g and 5a).

Hay and haylage (containing mostly alfalfa) significantly contribute to high groundwater footprint to aquifer area ratios in all aquifers in the Central Valley (Figures 6a–6e) and High Plains (Figures 6f–6h). This is due to a very high acreage in some counties and a high net blue water requirement. As the net blue water requirement was assigned to be that of the pasture crop functional type (supporting information Table S1), the ratio values for hay and haylage should be considered carefully however. Corn also has a relatively high groundwater footprint to aquifer area ratio in most aquifers, notably in the Northern and Southern High Plains (Figures 6f and 6g) and Delta, Eastside, and San Joaquin (Figures 6b–6d). In this case, it is more due to high acreage over most counties compared to hay and haylage since the net blue water requirement of corn is on average about 60–85% that of pasture, depending on aquifer system. The proportion of irrigated corn-for-grain acreage irrigated by groundwater is high in the High Plains, ranging from 73 to 97% in the states overlying the High Plains aquifer system (supporting information Table S6), except for Wyoming (44%), which only intersects a small portion of it though. Moreover, corn-induced groundwater stress may have been exacerbated by political and economic decisions. The U.S. government indeed introduced high-subsidy programs for corn, notably through the 2005 Energy Policy Act which called for increasing corn-derived ethanol production, which we believe might have led to an average 32% increase in corn acreage between 2002 and 2007 in all the states underlain by the High Plains aquifer system [*NASS*, 2009].

The crops that most often have the highest ratios (pasture, corn for grain, and hay and haylage) are those crops that cattle are mostly fed on. This is consistent with beef having the highest water footprint of all animal and crop products [*Hoekstra*, 2012]. On another hand, many crops for direct human consumption do

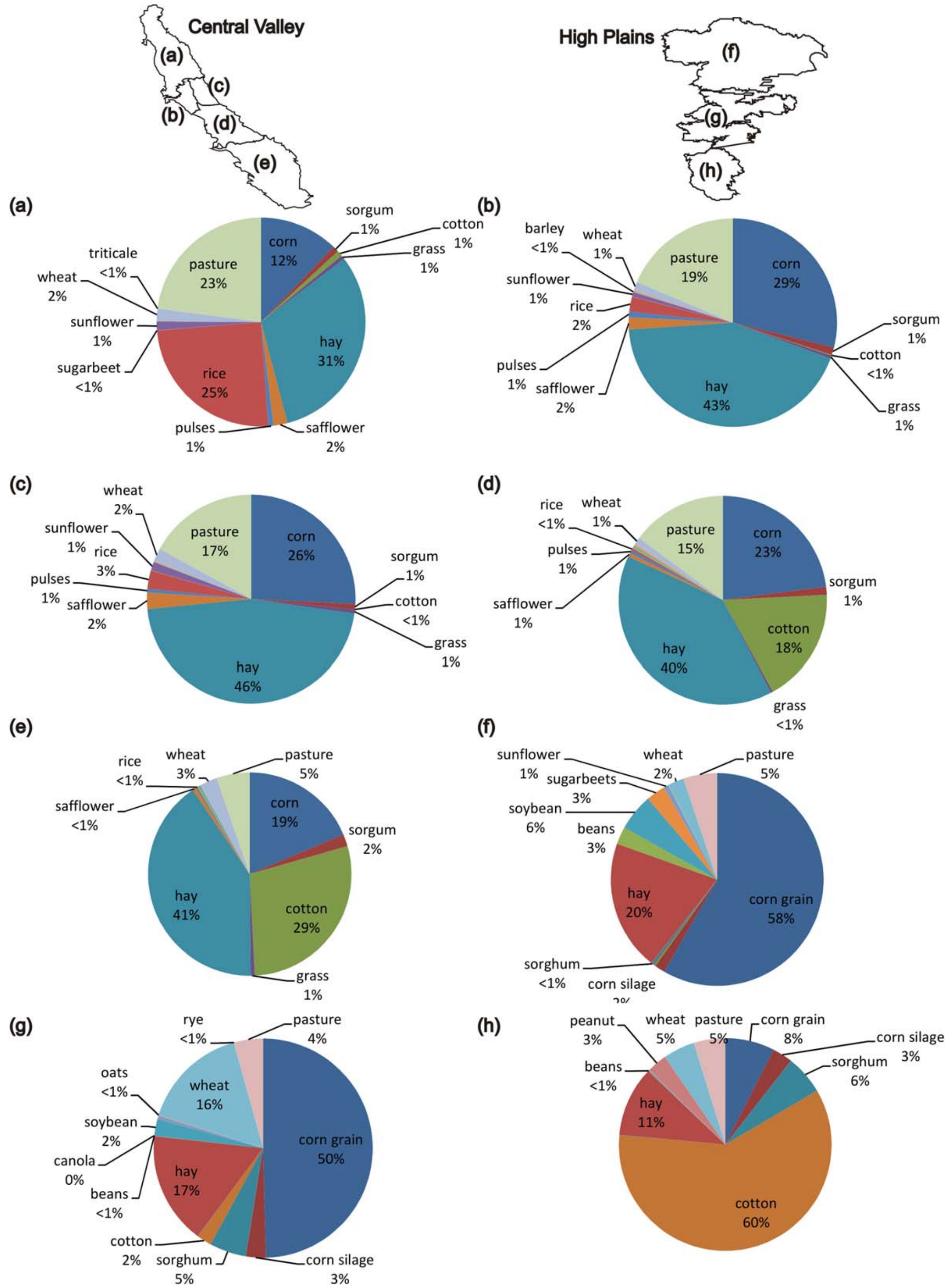

Figure 6. Contribution of crop types to total groundwater footprint to area ratio. Note that the colors are different between aquifers in the Central Valley and High Plains.

not individually yield a stressing ratio in either aquifer systems, for instance popcorn, beans, sugarbeets, sunflower, canola, or peanut (Figures 6a–6h).

Cotton has a high ratio in the Southern High Plains (9.2 $\pm$ 5.1; Figure 5e) as it is a prominent crop in Texas (Figure 6h), which accounts for $\sim$1/4 of total cotton production in the U.S. [*TSHA*, 2012] and where 88% of the irrigated cotton acreage is irrigated with groundwater (supporting information Table S6). Like hay and haylage, cotton was assigned the high net blue water requirement of the pasture crop functional type; its ratio should therefore also be considered carefully. Moreover, Texas has the largest share of cotton production in the U.S. ($\sim$30% in 2006) while 68% of U.S. cotton is exported to major textile-producing countries, mainly China, Turkey, and Mexico [*Robinson et al.*, 2006]. This suggests cotton exports contribute heavily to local aquifer stress, by being responsible for a groundwater footprint to Southern High Plains aquifer area ratio of $\sim$6.2. In California, $\sim$95% of cotton grown is exported [*WFPEI*, 2012], likely representing a groundwater footprint to aquifer area ratio of 0.2 to 0.3 in the Tulare and San Joaquin aquifers, imputable to cotton exports only. This is consistent with the U.S. being the third biggest country, in terms of volume, exporting cotton-virtual-water worldwide [*Hoekstra and Chapagain*, 2008]. Note that some of the U.S. cotton exported for processing will return to the U.S. as textile.

Rice acreage in the northern Central Valley is high (Figure 6a and supporting information Figure S2), almost the same acreage as corn for the entire Central Valley aquifer system. Nevertheless, rice only yields a low ratio there (0.08 $\pm$ 0.04; Figure 4h) despite being one of the highest in this area, which is due to only 18% of irrigated rice acreage using groundwater in California (supporting information Table S6). California moreover accounts for $\sim$20% of the U.S. rice production [*Sumner and Brunke*, 2003]. Exports of Sacramento Valley-grown rice thus represent a groundwater footprint to aquifer area ratio of 0.04. Californian rice is in majority high-quality medium japonica rice [*Sumner and Brunke*, 2003] that is used in sushi production. In 2001 and 2002, a mean of $\sim$46% of California-grown rice was exported, about half of which to Japan, $\sim$15% to Turkey and Jordan and $\sim$13% to Taiwan [*Sumner and Brunke*, 2003].

Note that total irrigation efficiency does not change significantly between crop types, ranging from 0.62 (rice) to 0.69 (barley) in the Central Valley and from 0.69 (rice and pasture) to 0.73 (corn for grain, wheat, and soybean) in the High Plains.

3.4. Applicability of the Method to Other Areas

This study was carried out for the Central Valley and High Plains aquifer systems partly because there are high-resolution agricultural and water use data readily available in the U.S. However, other areas of the world are likely to be much data-poorer. Our methodology and equations can easily be adapted to available data, which will determine the spatial resolution and accuracy of the estimated ratios of groundwater footprint to aquifer area.

Data in our methodology include irrigated acreage, proportion of irrigated acreage irrigated by groundwater, total irrigation efficiency, net blue water requirement, recharge, and environmental flow requirements (equations (1–3)). As LPJmL and PCR-GLOBWB are global models, access to the three latter data is ensured. However, the most accurate ratios should be obtained if recharge data taking into account local complexities are available; it is likely they are not crop-specific nevertheless. The need for large-scale hydrological models such as PCR-GLOBWB arises in places where local precise recharge data are not available and/or where the irrigation system is not overly complex, as evidenced by the good fit between modeled estimates and measurements in the central and southern parts of the High Plains. Gross efficiency values are also readily available for different regions of the world [*Rohwer et al.*, 2007] though they are available per nation and not crop-specific. Irrigated acreage can be derived from global data sets such as the one detailed in *Ramankutty et al.* [2008] coupled with *Portmann et al.*'s [2010], as previously used in LPJmL [*Gerten et al.*, 2011].

The proportion of irrigated acreage irrigated by groundwater can be derived from multiple sources [*de Graaf et al.*, 2014; *Döll et al.*, 2012]. Totals can be checked if locally derived groundwater data are available; if not, lower-spatial resolution groundwater abstraction data can also be used, such as the IGRAC database (http://www.un-igrac.org/) at nation-scale, which can be downscaled to obtain groundwater abstraction at finer resolutions [*Wada et al.*, 2010]. In this case however, one would need to have access to data on how much of this groundwater abstraction value is devoted to crop irrigation and to which aquifer or aquifer system.

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4. Conclusions

We calculated for the first time the groundwater footprint of 19 different crops (or crops amalgamations) and pasture at aquifer-scale in the two most used aquifer systems of the U.S., the Central Valley and High Plains. We used high-resolution agricultural data from U.S. government organizations along with simulated net blue water requirement, groundwater recharge, and environmental flow requirements from global models that we analyzed to obtain a consistent scale to calculate groundwater footprint estimates. Recharge estimates were also obtained from chloride and field data, and from a local groundwater model.

1. Hay and haylage and corn for grain are the crops that stress groundwater in both aquifer systems the most; the two account, respectively, for 18% and 56% of the total groundwater footprint in the High Plains, and for 38% and 19% of the total groundwater footprint in the Central Valley, highlighting the predominant role of crops grown for cattle feed in the depletion of the Central Valley and High Plains aquifer systems. Cotton, which is mostly exported, also account for a high ratio notably in the Southern High Plains.

2. Our estimates of groundwater footprint to aquifer area ratios are coherent with other studies in the High Plains though they are lower in the Central Valley compared to previous estimates of groundwater footprints to aquifer area ratio [*Gleeson and Wada*, 2013; *Gleeson et al*., 2012; *Scanlon et al*., 2012]. We believe those differences are attributable to surface water diversions for irrigation in California, which were not taken into account in previous estimates. We therefore consider our estimates to constitute a notable improvement, all the more since they encompass higher resolution agricultural data.

3. Uncertainties of recharge and irrigation application efficiency contribute the most to the total relative uncertainty of the groundwater footprint to aquifer area ratios. These two variables constitute $\sim$30% of the total relative uncertainty in both the Central Valley and High Plains aquifer systems. Other variables that contribute significantly to the total relative uncertainty include net blue water requirements, proportion of irrigated acreage irrigated with groundwater, and conveyance efficiency.

As described above, our methodology and equations can easily be adapted to other areas with different available data. The crop-specific methodology presented in this study allows a better evaluation of the impacts of economic policies on groundwater depletion, and in a broader way on the environment. In addition, the methodology can also show the consequences of consumer choices, such as eating red meat, on groundwater stress and can be used to educate the general public on the impact of their consumption choices. Subsequent improvements in the models we used would help further refine our estimates; for instance, considering more crop functional types and calibrate them to better validate results in the global hydrological model LPJmL or quantifying recharge and environmental flow requirements better and validating them against measurements. Groundwater and environmental flows are now being implemented in LPJmL [*Pastor et al*., 2013], which eventually will allow for internally consistent assessments of these processes without the need to combine different models. In an enhanced model version, recharge could also be crop- and irrigation method-specific since for instance paddy fields use mostly flood irrigation, which is likely to induce higher groundwater recharge than other irrigation methods. Running global or regional models (such as SWAT models) with input data available on a finer spatial resolution may also help in making estimates more accurate as a spatial resolution of 0.5° can be rather coarse for regional applications such as the one performed here. Furthermore, our estimates could be compared with the 2010 USGS Estimated Water Use in the U.S., when available, which should include a better quantification of what irrigation water use includes, or at least for a quantification of state estimates accuracy, notably since the guidelines for the next report specifically refer to this [*Kenny et al*., 2009]. Our methodology could be useful for hydrologists, water resource managers, and policy makers concerned with which crops are causing the well-documented groundwater stress in semiarid to arid agricultural regions around the world.

Notation

i	subscript indicating a given crop type (e.g., wheat).
co	subscript indicating data reported or downscaled to county-scale (more accurately co designates the scale of the intersection area between county and aquifer).
aq	subscript indicating data aggregated over aquifer-scale.
$GF_{i,aq}$	groundwater footprint, m^2.

A_{aq}	aquifer area, m^2.
R_{aq}	recharge, m/yr.
E_{aq}	environmental flow requirements, m/yr.
$Ga_{i,co}, Ga_{i,aq}$	groundwater abstraction for irrigation, m^3/yr.
Ga_{co}	total groundwater abstraction for irrigation, m^3/yr.
$B_{i,co}$	net blue water requirement, m/yr.
$Acr_{i,co}$	irrigated crop area, m^2.
p_i	areal proportion of irrigated crop area irrigated by groundwater, dimensionless.
$e_{i,co}$	total irrigation efficiency, dimensionless.
$e_{c_{co}}$	conveyance system efficiency, dimensionless.
e_{a_i}	application system efficiency, dimensionless.
e_m	management factor, dimensionless.

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