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High-Resolution Water Footprints of Production of the United States

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Key Points:
- We present the most detailed and comprehensive water footprints of production of any country to date
- Significant variability is evident in water footprints of production between locations and economic sectors
- Sourcing from water-efficient suppliers (indirect use) reduces water footprints more than changes to direct use

Supporting Information:
- Supporting Information S1
- Figure S1
- Figure S2
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Abstract The United States is the largest producer of goods and services in the world. Rainfall, surface water supplies, and groundwater aquifers represent a fundamental input to economic production. Despite the importance of water resources to economic activity, we do not have consistent information on water use for specific locations and economic sectors. A national, spatially detailed database of water use by sector would provide insight into U.S. utilization and dependence on water resources for economic production. To this end, we calculate the water footprint of over 500 food, energy, mining, services, and manufacturing industries and goods produced in the United States. To do this, we employ a data intensive approach that integrates water footprint and input-output techniques into a novel methodological framework. This approach enables us to present the most detailed and comprehensive water footprint analysis of any country to date. This study broadly contributes to our understanding of water in the U.S. economy, enables supply chain managers to assess direct and indirect water dependencies, and provides opportunities to reduce water use through benchmarking. In fact, we find that 94% of U.S. industries could reduce their total water footprint more by sourcing from more water-efficient suppliers in their supply chain than they could by converting their own operations to be more water-efficient.

1. Introduction

The United States is the largest producer of goods and services in the world (The World Bank, 2017). This economic activity relies on freshwater as a fundamental input to economic production (Rushforth & Ruddell, 2016; Wang et al., 2017). Despite the importance of water to the U.S. economy, it is often undervalued, inefficiently utilized, and overexploited (Marston & Cai, 2016). The first step toward sustainable water allocation (Hoekstra, 2014; Hoekstra et al., 2015) is to evaluate how it is currently being used (Chini & Stillwell, 2017). To obtain a meaningful understanding of how water resources are being used throughout the U.S. economy, detailed spatial and sectoral information are required (Blackhurst et al., 2010). To this end, we calculate the water footprint of production (Hoekstra & Mekonnen, 2012) for over 500 unique industries and goods within the United States at an unparalleled spatial resolution.

Water resources within the United States are projected to be increasingly stressed in the coming decades (Devineni et al., 2015). Growing and shifting populations, economic growth, expansion of the energy sector, and warming temperatures, shifting rainfall patterns, and shrinking snowpack due to climate change will alter water supplies and demands (Devineni et al., 2015). These issues are particularly concerning in the American Southwest, which is already water stressed and expected to face greater water scarcity in the coming decades (Schewe et al., 2014). Furthermore, increasing water allocations to meet environmental requirements could further strain existing water uses (Marston & Cai, 2016). It is essential to understand how water resources are currently being used in order to better evaluate how future water availability and demand will impact economic production activities.

Water use in the United States is heterogeneous, decentralized, and often politically contentious. This makes it challenging to meter water withdrawals and measure water consumption in a consistent way nationwide. Additionally, there are privacy concerns that prohibit government agencies from reporting some water uses. For this reason, there is a dearth of national, metered water use information for specific industries and locations (Chini & Stillwell, 2017). The USGS runs the National Water Use Information Program, which is a county-level inventory of water withdrawal *estimates*. This inventory has provided county-level water withdrawal information every 5 years since 1985 (Maupin et al., 2014). The USGS employs a variety of methods to estimate water use of an industry, including surveys, water meters, billing data, remote sensing, models, and water use coefficients. Water use coefficients—one of the most widely used methods for estimating water-use—allow for the estimation of water use based off a known variable (e.g., number of employees, amount of energy produced, area of cropland, etc.). However, the few water use coefficients that are published are often for a very narrow geographic area and industry, or they are too broadly defined at the national and sector level. This makes comparison of water use infeasible across different areas and industries.

The USGS water-use inventory primarily presents estimates of the use of water for relatively aggregated sectors of the economy (i.e., industry, mining, irrigated agriculture, livestock, aquaculture, and thermoelectric power) (Maupin et al., 2014). Grouping water-use estimates into coarse sectoral classifications masks important, yet poorly documented, water-use estimates at more refined industry levels.

Another shortcoming of the USGS database is that it does not estimate the contribution of rainfall in meeting national crop water requirements. Rainfall is the dominant water supply to crops (Mekonnen & Hoekstra, 2011a), although irrigation supplies from both surface and ground water sources are also important, especially in more arid climates. Rainfall water supplies provided via soil moisture are referred to as "green water," while water supplies from surface and groundwater sources are called "blue water" (Falkenmark & Rockström, 2004; Rost et al., 2008). Blue water is provided to agricultural water users via infrastructure, such as irrigation canals, center pivot spray systems, or groundwater pumps. Nonagricultural industries obtain surface and groundwater supplies through public and private piped infrastructure systems. Since nonagricultural industries only consume blue water, water-use estimates of these industries do not include green water.

Here, we define water use to be the consumptive use of water resources, following the approach of the water footprint literature (Hoekstra & Mekonnen, 2012). Traditionally, water footprint assessments have focused on agriculture, as it is responsible for 70% of withdrawals globally and is by far the largest consumptive user (Gleick & Palaniappan, 2010; Postel et al., 1996; Vörösmarty, 2000). We maintain the water footprint framework focus on consumptive water use in order to best capture the role of agriculture (Hoekstra & Mekonnen, 2012). Additionally, quantifying consumptive water use will provide a more accurate assessment of the amount of water required for production and enable us to better determine locations of water scarcity. This is because water withdrawals ignore the fact that return flows can be utilized many times. For instance, water withdrawals in the Colorado River Basin exceed renewable annual supply due to substantial reuse of return flows (Richter, 2014).

There is a growing body of literature that recognizes the important relationship between water resources and nonagricultural sectors of the economy, especially in urban areas (Paterson et al., 2015). This follows a broader trend of moving to finer spatial resolutions (Mayer et al., 2016; Rushforth & Ruddell, 2015, 2016) and industry-specific estimates of water use (Blackhurst et al., 2010; Wang & Zimmerman, 2016), including distinguishing between groundwater and surface water sources (Schyns et al., 2015). Yet, no national or global study to date combines the spatial resolution, sectoral specification, and water source delineation needed to provide a meaningful understanding of water use across the *full* economy. Subnational estimates of water use by water source for specific industries would be useful in environmental impact assessments, as noted by Blackhurst et al. (2010), and also enable more efficient water use by setting a localized water-use benchmark.

The purpose of this paper is to understand how water is used in specific U.S. industries and locations to produce the goods and services demanded by society. With this goal in mind, we calculate subnational *direct* water footprints of production (*WFP*; m^3/yr) for over 500 goods and services produced within the United States from 2010 to 2012. Here, direct *WFP* is defined as the volume of freshwater consumed during the present stage of production (i.e., the water incorporated into a product and/or evaporated during the production stage of analysis, which does not include cumulative water indirectly used through the supply chain). We also calculate the corresponding water footprint per unit of production (*WFU*). Presented results mostly represent *WFU* in terms of the value of production output in U.S. dollars ($WFU_{\$}$) but the database we make available also includes crop *WFU* in tons (WFU_{ton}) and energy *WFU* in terajoules (WFU_{TJ}). (A full list of symbols, terms, and definitions is presented in the Appendix A.) Importantly, we also calculate indirect water footprints using methods from the input-output literature (Leontief, 1970). By combining water footprint and input-out methods, we are able to distinguish the contribution of each source of water to the economic production of each sector.

For this study, we employ a data intensive approach that integrates water footprint and input-output techniques into a novel methodological framework. We leverage existing but disparate data sets on water use and economic production to resolve the water footprints of over 500 food, energy, mining, services, and manufacturing industries and goods. This study aims to answer the following questions: (i) How much surface water, groundwater, and rainwater is used to support the production of different industries and products across the United States? (ii) What industries and locations are the major consumers of water resources? (iii) What is the industry specific variance in water use across the country? (iv) Do industries depend more on water directly or indirectly through their supply chains? (v) Where does water used in U.S. food and energy production come from? The rest of the paper is organized as follows. We describe our methodology and highlight our primary data sources in section 2. Our results are presented and discussed in section 3. We conclude in section 4.

2. Methods

We utilize high-resolution and spatially explicit data sets of economic production and water use. We fuse disparate data sources together to consistently and comprehensively evaluate how the U.S. economy uses its water resources. Importantly, we distinguish surface and groundwater use in each industry, and the additional contribution of rainfall in agriculture. This data intensive approach enables us to produce the most detailed water footprint assessment of any nation to date. Table 1 outlines the major methodological contributions of our work and indicates how it compares with the current state-of-the-art with regards to spatial and sectoral resolution and water source delineation.

We calculate *consumptive* use of water resources. This represents a key difference with the USGS National Water Use Information Program, which estimates water withdrawals (Maupin et al., 2014). Quantifying water use in terms of withdrawals or consumptive use will provide a different accounting of use. We choose to follow the water footprint framework and focus on consumptive water use in order to most accurately capture the role of agriculture as a user of water (Hoekstra & Mekonnen, 2012). Additionally, quantifying water use in terms of withdrawals may overestimate water scarcity since return flows are able to be reused numerous times.

We reemphasize that we estimate *direct* water footprints of production and only calculate the water consumed in the immediate production process. For this reason, our results cannot be directly compared with studies that estimate total (i.e., direct and indirect) water footprints of production. However, our direct *WFU* estimates can be used within environmentally extended input-output (EEIO) models, as we demonstrate later. Note that we only include freshwater use in our analysis. Some industries and locations may use saline water, which we do not capture. Maupin et al. (2014) estimated that in 2010 saline water comprised 13% of the nation's total water withdrawals, with 90% of that attributed to thermoelectric power generation. We detail specific methods for each economic sector below.

2.1. Data

We leverage existing U.S. data sets on water use and supply and economic production. Table 2 lists the major data products utilized in this study by water use category. Water use categories roughly follow those available in the USGS database: public supply, industrial self-supplied, domestic self-supplied, mining, irrigation, livestock, aquaculture, and thermoelectric power (Maupin et al., 2014). Self-supplied water refers to water that is obtained directly from a water body by the user. This is distinct to public supplied water, which is withdrawn from the initial source and delivered to users by a water utility. USGS public supply and industrial self-supplied water use categories fall under the "Commercial, Industrial, and Institutional" (CII) water use category in Table 2. We broadly define the USGS "Irrigation" category as "Crops" since we include water

Table 1
Comparison of This Study to the State-of-the-Art With Regards to Spatial Resolution, Water Source Delineation, and Product/Industry Specification for Each Water Use Category

Sector		Spatial resolution	Water source delineation	Product/industry specification
Crops	State-of-the-art	5 x 5 arc minutes *WFP* and state virtual water contents (Mekonnen & Hoekstra, 2011a)	Green and blue water (Mekonnen & Hoekstra, 2011a)	146 crops (Mekonnen & Hoekstra, 2011a)
			Streamflow, reservoirs, and/or aquifers/nonlocal water sources (Hanasaki et al., 2010; Wada et al., 2014)	
			Natural lakes, surface water tributaries, shallow groundwater, and deep groundwater (Mayer et al., 2016)	
			Renewable and nonrenewable groundwater (Dalin et al., 2017)	
	This study	County. Improved on Mekonnen and Hoekstra (2011a) estimates by using higher-resolution empirical data on agriculture production and irrigation patterns.	Green water, surface water, and groundwater	141 crop were estimated (5 of the 146 crops in Mekonnen and Hoekstra (2011a) global study are not grown in the United States or sufficient data are not available).
Livestock	State-of-the-art	5 x 5 arc minutes (downscaled from national level). (Mekonnen & Hoekstra, 2012)	Reservoirs, streamflow, nonrenewable and nonlocal blue water/groundwater (Hanasaki et al., 2010; Wada et al., 2014)	Eight livestock animals (Mekonnen & Hoekstra, 2012)
	This study	County and state	Surface water and groundwater	Estimates for nine (8) livestock animals.
Thermoelectric	State-of-the-art	Power plant (Diehl & Harris, 2014; EIA, 2017a)	Specific water body (e.g., Chena River) (Diehl & Harris, 2014; EIA, 2017a)	15 different generator technologies/fuel sources and 9 circulation categories. (Diehl & Harris, 2014; EIA, 2017a)
	This study	Power plant, aggregated to county.	Aggregated to fresh surface water and groundwater	Aggregated to five fuel types and two circulation categories.
Mining	State-of-the-art	County[a] (Maupin et al., 2014)	Fresh and saline surface water and groundwater (Maupin et al., 2014)	11 mining sectors (Blackhurst et al., 2010)
	This study	County	Fresh surface water and groundwater	*WFU* for 15 mining sectors. *WFP* represent aggregate value across all mining operations.
Aquaculture	State-of-the-art	County[a] (Maupin et al., 2014)	Fresh and saline surface water and groundwater (USDA, 2014a)	39 aquaculture species (Pahlow et al., 2015)[b]
	This study	State	Fresh surface water and groundwater	Represented as one sector
Commercial, Industrial, & Institutional (CII)	State-of-the-art	Point, aggregated to the county scale (Mayer et al., 2016)[c]	Lakes, surface water tributaries, shallow groundwater, and deep groundwater (Mayer et al., 2016)	~380 industries (Blackhurst et al., 2010)
	This study	117 state and sub-state areas	Surface water and groundwater. Account for nonrevenue water losses and interregion water transfers.	378 industries

[a]Consumptive values are not available at this scale, only withdrawals. [b]Only calculates indirect water footprints. [c]Study does not provide national coverage, nor does it provide fine sectoral resolution.

use estimates of both irrigated and rainfed crops. Domestic water use is excluded from our analysis since we are only concerned with water use related to economic production.

Agricultural (USDA, 2016) and business production data (U.S. Bureau of Economic Analysis, 2017) are sometimes suppressed by government agencies for privacy concerns. Instances of data suppression are flagged within the data set, indicating that there are limited producers in that geographical area. Data suppression

Table 2
Primary Data Sources

Water use category	Data product purpose/description	Source	Data type	Finest spatial resolution	Data year
Crops	Crop production (irrigated and rainfed); Crop prices	USDA (2014b)	Production	County	2012
Crops	Crop blue and green water requirements	Mekonnen and Hoekstra (2011b)	Water	5 x 5 arc minute	1996–2005
Crops	Groundwater and surface water irrigation fractions	Maupin et al. (2014)	Water	County	2010
Aquaculture	Groundwater and surface water utilization; Aquaculture sales and production method	USDA (2014a)	Water; Production	County	2012, 2013
Aquaculture	Average annual open water surface evaporation	Farnsworth et al. (1982); Farnsworth and Thompson (1982)	Water	Point/isohyetal	1919–1979
Mining	Water withdrawals and consumption coefficients	Maupin et al. (2014)	Water	County	1995, 2010
Mining	Water use coefficients	Meldrum et al. (2013); University of Tennessee Center for Clean Products (2008); Spang et al. (2014); Norgate and Lovel (2004); Mudd (2008, 2010); Norgate and Haque (2010)	Water	Point	Varies
Mining	Non-fuel mineral prices	Survey (2017)	Production	State	2012
Mining	Fuel prices	EIA (2017b, 2017c, 2013a, 2013b)	Production	State	2012
Thermoelectric	Water withdrawals and consumption	Diehl and Harris (20140	Water	Plant	2010
Thermoelectric	Plant fuel type	EIA (2017a)	Production	Plant	2010
Thermoelectric	Electricity prices	EIA (2013c)	Production	State	2012
Hydropower	Water consumption	Grubert (2016)	Water	Region	2010–2014
Livestock	Water withdrawals	Maupin et al. (2014)	Water	County	2010
Livestock	Livestock production and prices	USDA (2014b)	Production	County	2012
Livestock	Water use coefficients	Lovelace (2009a); Buchwald (2009); Carter and Neitzert (2008); Pugh and Holland (2015); Sargent (2011); Longworth et al. (2013)	Water	State	Varies
Commercial, Industrial, and Institutional	Water withdrawals	Maupin et al. (2014)	Water	County	2010
Commercial, Industrial, and Institutional	Direct water requirement coefficients	US Bureau of Economic Analysis (2013c); Statistics Canada (2017a, 2017b)	Water	Nation	2007, 2011, 2013
Commercial, Industrial, and Institutional	Water transfers	Numerous (Appendix Table B1)	Water	Point	Varies
Commercial, Industrial, and Institutional	Consumption coefficients	U.S. Census Bureau (1986)	Water	Nation	1982
Commercial, Industrial, and Institutional	Nonrevenue water fraction	Numerous (supporting information Table S2)	Water	City	Varies
Commercial, Industrial, and Institutional	Industry revenue and employment	U.S. Census Bureau (2017)	Production	County	2012

is more prevalent at smaller spatial scales (e.g., counties) and among specialty producers. For instance, production data of the only almond farmer in Greeley County, Nebraska is flagged since reporting this data would reveal information related to that specific farmer. We take advantage of the hierarchical structure of the data by industry/product and geography to approximate suppressed values when encountered. The almond production of the sole farmer in Greeley County, for example, was estimated by subtracting the sum of all Nebraska county almond production from the state-level production value provided by USDA (2016). The difference between the state total and the sum of all counties is uniformly distributed amongst all Nebraskan counties with suppressed almond production records. While similar approaches have commonly been applied in the literature (Isserman & Westervelt, 2006; Marston et al., 2015; Marston & Konar, 2017; Rushforth & Ruddell, 2015, 2016; Smith et al., 2017), our study would nonetheless benefit from a complete original data set.

Data availability varied by sector and spatial scale. We utilize the finest spatial resolution provided by each data source. We restrict our study to the time period of 2010–2012 because this is when production data—a critical input variable—are most widely available within the United States. In addition to production data, water footprint estimates depend on measures of consumptive water use rates, such as crop ET or water use coefficients. Consumptive water use rates were generally averaged over several years to avoid the effects of interannual climate variability on our estimates. Thus, our results represent typical (i.e., under representative local climate conditions) water consumption associated with economic production occurring during our study period. Importantly, we use average crop ET rates to smooth over climate extremes that significantly impact water use within crop production. We do not include water used for golf courses and other recreational purposes (such as duck hunting or reservoirs purposed for recreation) due to incomplete data. Additional details relating to data of each economic sector are found below.

2.2. Water Footprints of Crop Production

The water footprint of crops was estimated using a dynamic water balance model (Mekonnen & Hoekstra, 2011a). The model computes daily soil water balance and calculates crop water requirements and actual crop water use, allocating crop water use to rainfall and irrigation sources. Water stress and nonoptimal crop growth conditions are considered in the model. The model only accounts for the evapotranspiration (ET) requirement of each crop, not other potential consumptive water uses such as frost protection, field preparation, and evaporation losses from irrigation reservoirs and distribution canals. Although these water uses are generally small in relation to ET requirements, their exclusion means that our estimates are conservative (Mekonnen & Hoekstra, 2011a).

The model has been used to estimate crop water footprints globally (Hoekstra & Mekonnen, 2012; Mekonnen & Hoekstra, 2011a). To do this, the model was run globally at a spatial resolution of 5×5 arc minute for 146 crops for the time period 1996–2005 (Mekonnen & Hoekstra, 2011a). For this study, we select the pixels within the United States and restrict our analysis to the 141 crops grown within the United States. While our model provides global coverage, input climate data were taken from a study that utilizes local meteorological stations to specify climate variables (Mitchell & Jones, 2005). Mekonnen and Hoekstra (2011a) utilize a global data set of agricultural areas and irrigation to estimate water footprints. Here, we improve upon these global estimates with crop data available for the United States from the U.S. Department of Agriculture (USDA, 2014b). We average pixel level estimates of crop water requirements (m^3/ha) from Mekonnen and Hoekstra (2011a) to the U.S. county scale in order to match the spatial scale of U.S. government databases. This process provides crop-specific water requirements at the county-year scale (m^3/county/yr) by rainwater and irrigation supplies. Note that this is the only economic sector in this study for which we include rainwater.

To determine high-resolution *WFP*, we utilize information on the irrigated and nonirrigated areas for each crop and county from the USDA. The USDA provides information on the crop-specific harvested area for each county, including those in multicropping systems, and indicates the fraction that is irrigated and rainfed (USDA, 2014b). Since multicropping occurs on only 2% of total U.S. cropland (Borchers et al., 2014) and the growing season of each respective crop typically aligns with the growing seasons used in our model, multicropping should not significantly impact our results. We multiply the modeled crop water use transformed to county scale (m^3/county/yr) by the USDA county-crop-specific area (rainfall and irrigation water use for irrigated areas; only rainfall water use for rainfed areas). For many berry, orchard, and vegetable crops, USDA does not specify whether the crop was rainfed or irrigated. In these cases, we estimate county-level irrigated and rainfed areas. We do this by taking the product of the crop area and the irrigated/rainfed area fraction of the broader crop category to which it belongs (e.g., blackberries use the irrigated fraction of berries, apples use orchard, and celery uses vegetables).

Next, we attribute the blue water footprint from irrigation to surface and groundwater sources. We use data from Maupin et al. (2014) that specifies the volume of surface and groundwater used for all irrigation in each county to determine the irrigation fraction from surface and groundwater sources. Here, we assume that all crops grown within a county receive irrigation from surface and groundwater in the same proportions. This approach enables us to estimate county-level, crop-specific footprints of production by water source for 141 crops. County-level, crop-specific data on surface and groundwater utilization would improve our estimates, but this data are not available.

We also calculate $WFU_{\$}$ and WFU_{ton} for 133 crops (data limitations prohibited inclusion of some minor crops included in *WFP* assessment) for all states within the United States. County-level *WFU* are calculated for crops that USDA provides county-level crop yield records. Note that our estimates represents the theoretical crop water use of all crops in all locations based upon average climatic conditions. However, this does not mean that all crops are grown in all locations. Since we use crop production data from USDA (2014b), we only show *WFU* corresponding to where a crop is actually grown. We quantify the WFU_{ton} by dividing the modeled water consumption (ET) per crop area (m^3/ha/yr) for each crop by its yield (ton/ha), which gives water consumption per ton of production (m^3/ton). When determining average crop yields, we account for nonbearing fruit trees, nut trees, and other crops that require water but may not produce a yield in a given year. This allows us to reflect the total water allocated to a specific crop. Next, we divide the previous quotient by crop prices ($/ton) to obtain $WFU_{\$}$ (m^3/$). Crop prices, production, and yield data come from USDA 2012 Census of Agriculture (USDA, 2014b). National crop prices were used when state prices were not available.

The following equations describe how *WFP*, $WFU_{\$}$, and WFU_{ton} were calculated for each crop in every state and/or county in the United States.

$$WFP_{m,n,o,p} = ET_{m,n,o,p} \cdot area_{m,n,p} \tag{1}$$

$$WFU_{ton,m,n,o} = \frac{ET_{m,n}}{yield_{m,n}} \tag{2}$$

$$WFU_{\$,m,n,o} = \frac{WFU_{ton,m,n,o}}{price_{m,n,o}} \tag{3}$$

where *m* is either the county or state where the water is utilized, *n* is the crop consuming the water, *o* is the water source (i.e., green water, surface water, or groundwater), *p* specifies whether the crop area (*area*) is irrigated or strictly rainfed, *ET* is the evapotranspiration associated with crop production, *price* is the crop market price, and *yield* is the crop yield.

2.3. Water Footprints of Aquaculture Production

The water footprint of aquaculture depends on the production method. In 2013, there were 4,129 aquaculture operations in the United States. The primary production methods were ponds (36%), tanks (17%), raceways (9%), cages and pens (7%), and other methods (30%) (USDA, 2014a). Each of these methods requires varying levels of water use. Here, we only consider consumptive water use, so only quantify the water evaporated from ponds. The consumption of water associated with pass-through methods (such as raceways) or instream harvesting (as sometimes the case with cages and pens) is negligible. Similarly, water withdrawn for oxygenation, waste discharge, temperature control, seasonal restocking, or seepage losses are often returned to local water sources, and are thus not considered a consumptive water use.

To quantify the water footprint of aquaculture, we use the USDA 2013 Census of Aquaculture (USDA, 2014a) and 2012 Census of Agriculture (USDA, 2014b). Data limitations prohibit county level estimates, instead requiring us to provide state scale values. Moreover, aquaculture sales and distributions were suppressed in nine states (representing 2.2% of the U.S. total), as were freshwater surface area used in aquaculture (representing 1.7% of the U.S. total). Our estimates are conservative since state values corresponding to these missing records are not represented in our analysis.

WFP for aquaculture were quantified by multiplying the total surface area of water in production by the long-term average open water evaporation rates for each state. We determine low, high, and production area weighted open water evaporation rates (mm/yr) for each state based on long-term climate records from the National Oceanic and Atmospheric Administration (NOAA) (Farnsworth et al., 1982; Farnsworth & Thompson, 1982). For production area-weighted evaporation estimates, we weight the evaporation rates by the area of aquaculture production. For example, nearly all aquaculture in Texas occurs near the Gulf Coast, where open water evaporation rates are relatively low for the state. Our approach produces a production area weighted evaporation rate that is lower than a simple state average.

We estimate surface and groundwater contributions to *WFP* of aquaculture. To do this, we follow the approach of Lovelace (2009b), and use the number of aquaculture operations reporting surface and groundwater use within each state to delineate *WFP* by source. $WFU_{\$}$ was calculated by dividing state *WFP* by aquaculture revenues from USDA (2014a).

2.4. Water Footprints of Livestock Production

Livestock directly use water for drinking, sanitation, cooling, waste disposal, onsite feed mixing, and other service activities. We estimate *WFP* for the following livestock categories: dairy cows, beef and other cattle, hogs and pigs, laying hens, broilers and other chickens, turkeys, sheep and lambs, goats, and equine (including horses, ponies, mules, burros, and donkeys). Estimates of water usage by specialty animals, such as alpacas and ostriches, are not included in this study. Specialty livestock represent less than 1% of all livestock in the United States (USDA, 2014b).

We assume that all water utilized in livestock production is consumed (i.e., no return flows). Drinking water and water used for feed mixing are both directly consumed by the animal. Some of this water reenters the watershed through excretion. We do not account for animal excretion due to difficulties in assessing the quantity, location, and quality of this excretion. Moreover, in nonindustrial livestock systems, excretion is typically released randomly in fields where the water portion is evaporated before it reenters a water body (thus, effectively consumed by the definition of *WFP*). In industrial systems, service runoff is often captured in lagoons where it is treated and/or much of the water evaporates.

Water-use coefficients are required to estimate livestock direct water footprints since livestock water use is not metered or reported (Lovelace, 2009a).The *WFP* of livestock was calculated by multiplying county livestock population data from the 2012 Census of Agriculture (USDA, 2014b) by animal-specific water-use coefficients from national (Lovelace, 2009a) and state reports (Buchwald, 2009; Carter & Neitzert, 2008; Longworth et al., 2013; Pugh & Holland, 2015; Sargent, 2011). Livestock water use varies between States depending on farming practices and production methods, climatic conditions, and water availability. Some states have developed water-use coefficients for internal use but do not publish them to protect the privacy of livestock producers. Other states do not estimate state-specific coefficients, instead choosing to use the median water-use coefficient of each livestock category (e.g., as reported in Lovelace 2009a), when reporting livestock water use for the USGS run National Water Use Information Program (Maupin et al., 2014).

We use publicly available state livestock water-use coefficients when available. When state water-use coefficients are not available, we estimate them. First, to estimate state coefficients we start by using the national median water-use coefficients (Lovelace, 2009a). For each state, the national coefficients are scaled so that the product of these coefficients and the state's animal inventory (USDA, 2016) equal the state's total water use as estimated in the USGS National Water Use Information Program (Maupin et al., 2014). This approach allows us to estimate water-use coefficients for each state by replicating the approach used by USGS (Lovelace, 2009a), but in reverse (i.e., we calculate water use coefficients for each animal, not total water use). The water-use coefficients are then checked to ensure they fall within the range of potential values reported by Lovelace (2009a). Next, water-use coefficients were partitioned into surface and groundwater using the fraction of total livestock withdrawals from each source in the USGS National Water Use Information Program (Maupin et al., 2014).

Water use for each livestock category was estimated for each U.S. county for the year 2012 (i.e., the most recent year of the USDA census). We multiplied state-specific water-use coefficients for each livestock category by the population within each county. Here, we assume that livestock inventories remain relatively stable throughout the year (i.e., livestock sold for slaughter or those that die are replaced). In this way, we estimate county level *WFP* for 2012 in terms of surface and groundwater for each livestock category.

To calculate $WFU_{\$,}$ we first determine the livestock lifetime direct water use. The average lifespan of each livestock category is calculated as the inverse of the inventory turnover rate. For example, the U.S. hog inventory in 2012 was 66,026,785 and the national hog slaughter total for 2012 was 113,246,600. This means that inventory turnover rate is 1.72 hogs per year (i.e., 113,246,600/66,026,785) and, thus, the average hog lifespan is 0.58 years (i.e., 1/1.72). The livestock lifetime direct water use is the product of the daily water use coefficient and the lifespan of each livestock category. The livestock lifetime direct water use is then divided by the total livestock value and its derived products. For example, the total output value of a dairy cow is both the milk it produces and its slaughter price. This represents the $WFU_{\$}$ of each livestock category (m^3/\$).

$$WFP_{m,o,q}=L_q \cdot WUC_{m,o,q} \cdot N_{m,q} \tag{4}$$

$$WFU_{\$,m,o,q}=\frac{WFP}{SP_{m,q} \cdot N_{m,q}+SAP_{m,q}} \tag{5}$$

where m is the county or state where the livestock utilizes water, o is the water source (i.e. surface water or groundwater), and q is the animal consuming water. The length of time an animal utilizes local water resources is represented by L, N is the number of animals, SP is the animal slaughter price, and SAP is the total sale value of secondary animal products, such as wool, milk, and eggs.

2.5. Water Footprints of Commercial, Industrial, and Institutional Production

Commercial, industrial, and institutional (CII) water use represent the water required to manufacture or process goods and provide services. Industrial water use is primarily used for heating and cooling (heat transfer), processing, fabricating, washing, diluting, or is incorporated into a product (e.g., concrete product manufacturing). Institutional and commercial water use is water used by motels/hotels, restaurants, hospitals, retail and grocery stores, office buildings, warehouses, schools, government, and other commercial facilities to serve the requirements of customers, employees, members, visitors, and/or students, as well as to maintain the premises (including heating, cooling, cleaning, and landscape irrigation).

We determine *WFP* for 378 CII enterprises across 117 geographical areas in the United States. The number of CII enterprises included in this study is restricted to those specified in the U.S. Bureau of Economic Analysis input-output direct requirement table (U.S. Bureau of Economic Analysis, 2017). The 117 areas align with the Commodity Flow Survey (CFS) boundaries (U.S. Census Bureau, 2014), although a few are merged together. Henceforth, we refer to these 117 areas as CFS Areas. These CFS Areas include major U.S. cities, which are responsible for 78% of national CII economic activity. Nonurban CFS Areas typically represent "remainder of states." Figure 6 shows the boundaries of our analysis. We employ a methodology similar to Blackhurst et al. (2010) but we improve upon their methods in the following ways: (i) we report subnational values as opposed to only national statistics; (ii) we report values in terms of consumptive water use; (iii) we account for nonrevenue water losses; and (iv) we quantify a range of potential values, capturing uncertainty in our estimates. A graphical overview of our methodology is provided in the supporting information.

Like Blackhurst et al. (2010), we estimate CII water footprints by beginning with estimates of water withdrawals from the USGS National Water Use Information Program (Maupin et al., 2014). Note that Blackhurst et al. (2010) used USGS withdrawal data from 2000, but that we employ the 2010 data set. CII water users retrieve their water from public supply and/or self-supplied surface and groundwater sources. Public supply systems are defined as public or private water providers having a minimum of 15 service connections or serving at least 25 people. Public supply water is often locally sourced but can be conveyed across county or even state boundaries. Industries that supply their own water typically locate near a water body due to the nature of some water rights (e.g., riparian water rights require adjacency to the water body) and the high cost of transferring water. We utilize different methods to disaggregate water use to each industry depending on the water supply source (public supply or self-supplied). The total water use of each industry is the sum of its self-supplied and publicly supplied water.

We begin by disaggregating public supply water withdrawals and deliveries to specific industries. As noted previously, the location public supply facilities withdraw water may not be the place where the water is used. Yet, this study is focused on where and who uses the water, not necessarily the initial location of the water source. Thus, the first step is to determine the net water usage within each CFS Area, after accounting for water imports and exports. CFS Areas stretch beyond traditional metropolitan boundaries, typically fully encompassing all major water distribution systems. Thus, in most instances water withdrawals and water use are contained within the same geospatial boundary. However, there are several instances of large water transfers across CFS Area boundaries. Journal searches, review of city, state, and national reports, querying online databases, and personal communications with personnel at state and federal agencies were employed to identify and quantify water transfers (full list of sources provided in the Appendix, Table B1). Water transfers were subtracted from the exporting area and added to the importing area. Accounting for water transfers allows for a more accurate representation of water utilization of each area than previous bottom-up studies (e.g., Rushforth & Ruddell 2015, 2016). In places like New York City, where all water is from nonlocal sources, this methodological step is critical if we are to properly attribute water to the proper end use. Nonetheless, it is likely that there are some small volume inter-CFS Area transfers that are missing from our database. Furthermore, water transfer volumes can vary between years. Most water transfer values align with our study period; however, data limitations lead us to use water transfers outside our study window in some instances.

Once the total public water supply utilized in each area was determined, we calculate how much of that water was delivered to CII users. First, nonrevenue water (NRW) was subtracted from total public water supplies. NRW is water that is lost through real losses (e.g., leaks), apparent losses (e.g., theft or faulty metering), or authorized but unbilled water use (e.g., street cleaning or fire-fighting). This water is withdrawn and enters the distribution system but is not delivered to a paying customer. Web queries of major metropolitan water districts, governmental and American Water Works Association (AWWA) reports, and personal communication with water district staff were used to estimate NRW as a percent of total produced water for each CFS Area. When a recent NRW value was not available for a CFS Area, the median value of 15% was used, as recommended by Solley et al. (1998). In this way, we determine the quantity of water actually delivered to paying CII users.

Next, water deliveries to domestic users was deducted. Domestic water deliveries were estimated for each county in Maupin et al. (2014). These deliveries represent the water that reaches and is used by residential consumers. This is typically estimated using surveys, meter and billing data, and/or water use coefficients. We aggregate domestic water use from the county to the CFS Area and then subtract this from the total water sold within the CFS Area. We assume that the remaining water is all sold to CII users. The last time it was recorded (Solley et al., 1998), only 0.3% of public water supply deliveries went to thermoelectric power generation. It was therefore considered negligible. The following equation summarizes how we calculate total CII water deliveries:

$$CIID_{CFS} = (PS_{CFS} \pm NWT_{CFS}) \cdot (1 - NRW_{CFS}) - DOD_{CFS} \tag{6}$$

where *CIID* is water deliveries to commercial, industrial, and institutional users within a given *CFS* Area, *PS* is public supply withdrawals, *NWT* is net water transfers, *NRW* is the fraction of produced water that is nonrevenue water, and *DOD* is water deliveries to domestic users.

Total water deliveries to CII users within a CFS Area were allocated to each industry according to their purchases from the "water, sewage, and other systems sector" (U.S. Bureau of Economic Analysis, 2017). This approach assumes a uniform pricing structure across all users and that the price of water relative to sewage is also constant across all industries within a CFS Area. The assumption of a uniform price structure is necessary because data on the specific water pricing structure of all 151,000 public water systems in the United States is not available. For this reason, we follow the approach of Blackhurst et al. (2010), who assume a uniform price structure. This is a realistic assumption because a uniform price structure is the most common price structure amongst U.S. water utilities (EPA, 2009). The shortcoming of this assumption is that we will imprecisely estimate water use when an increasing or decreasing block rate structure is in place. If an increasing block rate structure is in place, our assumption of a uniform pricing structure will underestimate water use of small users, while potentially overestimating the water use of large users. If a declining block rate structure is in place, we will overestimate the water use of small users, while potentially underestimating the water use of large users. Note that many large users self-supply their water through direct extraction from rivers or aquifers, so their estimated water use would not be impacted by this assumption.

Water purchases per unit of production (i.e., direct requirement coefficients) were taken from the U.S. Bureau of Economic Analysis input-output direct requirement table (U.S. Bureau of Economic Analysis, 2017). The product of an industry's direct requirement coefficient and its reported revenue (U.S. Census Bureau, 2017) yield the total water purchased by that industry within a CFS Area. These water purchases were normalized by dividing them by the sum of all CII water sales in the CFS Area. The fraction of total water purchases allocated to an industry is then multiplied by the CII water deliveries. This gives an industry-specific estimate of publicly supplied water deliveries ($S_{i,CFS}$) for each *CFS* Area, as depicted in the following equation:

$$S_{i,CFS} = \frac{WP_{i,CFS}}{\sum_{i \in CII} WP_{i,CFS}} \cdot CIID_{CFS} \tag{7}$$

where *WP* are water purchases of a given sector *i* within a particular *CFS* Area.

Industrial water use is often self-supplied, not purchased. Estimates of industrial self-supplied water withdrawals from Maupin et al. (2014) were allocated to industries manufacturing and processing food and beverage products, textiles, wood and paper, metals, minerals, petroleum, plastics, machinery, electronics, and other goods. Existing industrial water-use coefficients were used to first estimate the water withdrawals of each industry. These estimates were then scaled to match the reported total industrial self-supplied water withdrawal (Maupin et al., 2014). In this way, our estimates are grounded to actual measurements of water use. Following the approach of Blackhurst et al. (2010), industrial water withdrawals per employee were taken from recent Canadian water use and employment surveys (Statistics Canada, 2017a, 2017b). U.S.-based estimates of water use per employee do exist (Davis et al., 1987). Yet, more recent estimates from Statistics Canada (2017a) better capture the potential changes in water use due to the significant changes and automation in the manufacturing sector over the last few decades. For each CFS Area, coefficients of water use per employee were multiplied by the number of employees (U.S. Bureau of Economic Analysis, 2017) within the corresponding industry. Water withdrawal estimates were scaled to match self-supplied industrial water withdrawals (Maupin et al., 2014). The industrial self-supplied water allocation procedure is summarized as follows:

$$IW_{i,CFS} = \frac{WC_{i,CFS} \cdot E_{i,CFS}}{\sum_{i \in I} WC_{i,CFS} \cdot E_{i,CFS}} \cdot TIW_{CFS} \tag{8}$$

where *IW* is the water withdrawals of a specific industry, *WC* is the coefficient of water withdrawal per employee for industry i, *E* is the number of employees, and *TIW* is the total industrial self-supplied water withdrawals within a *CFS* Area.

Finally, we add self-supplied water use and water deliveries from public supply to derive the total water use of each industry for each CFS Area. We assume that each industry within a CFS Area uses the same fraction of surface and groundwater. The surface water (groundwater) fraction was calculated by summing all self-supplied withdrawals or public supply deliveries of surface water (groundwater) within a CFS Area and dividing this by the corresponding total self-supplied withdrawals or public supply water deliveries from all water sources (as reported by Maupin et al., 2014). However, their total consumptive use of water from each source may differ. Industry-specific consumption coefficients (U.S. Census Bureau, 1986) are applied to determine *WFP* for each industry. *WFP* is divided by the revenue of each industry to calculate $WFU_{\$}$. Using this methodology, we estimate 378 industry-specific footprints for 117 U.S. areas.

2.6. Water Footprints of Thermoelectric and Hydropower Production

Thermoelectric power plants withdraw more water than any other U.S. sector (Maupin et al., 2014). Thermoelectric power plants convert water to steam to turn turbines and produce electricity. The largest use of water by thermoelectric plants, however, is in cooling the steam. Water withdrawals and consumption differ by fuel type utilized by the power plant (i.e., fossil fuels, nuclear fission, or geothermal energy) but the major factor behind differences in water withdrawals and consumption is whether the plant uses open or closed-loop cooling (Macknick et al., 2012). Open-loop cooling systems (found predominately among older plants) withdrawal 96% more water than a closed-loop cooling system (DeNooyer et al., 2016). However, closed-loop systems, which recirculate water through the system many times, consume around 60% more water than an open-loop cooling system.

The U.S. Energy Information Administration (EIA) is the chief U.S. agency responsible for reporting water withdrawals and water consumption associated with thermoelectric power production. However, EIA thermoelectric water use estimates have been criticized due to data inconsistencies, incompleteness, and data quality issues (Averyt et al., 2013; Diehl et al., 2013). Moreover, a report by the USGS (Diehl & Harris, 2014) shows that most of the reported EIA values of both withdrawal and consumption were not thermodynamically plausible. Withdrawals reported by EIA were 24% higher than modeled estimates, while reported consumption was 8% lower (Diehl & Harris, 2014). Given the noted shortcomings of the EIA data set, we use plant-level modeled estimates of consumptive water use by water source (surface or groundwater) and cooling system from Diehl and Harris (2014). These estimates are constrained and validated against collected data and heat and water budgets, which consider electricity production and fuel use. Fresh water consumption is summed across all thermoelectric plants within a county to arrive at county level *WFP* estimates.

Next, we calculate $WFU_{\$}$ and WFU_{TJ} for each state by fresh water source. At the power plant level, water use can be further distinguished by cooling system and fuel type. The *WFP* of each power plant is normalized by net energy generation [TJ] from (Diehl & Harris, 2014; U.S. Energy Information Administration (EIA), 2017a), which provided estimates of WFU_{TJ}. State level WFU_{TJ} was calculated by summing all plant *WFP* and dividing by the corresponding total net energy generation. The state WFU_{TJ} was divided by state level electricity prices (EIA, 2013c) to calculate $WFU_{\$}$ ($m^3/\$$). Values of $WFU_{\$}$ are constrained to the state scale since this is the finest spatial resolution electricity prices are available. Importantly, substate variability in electricity prices would not influence our estimates of the water footprint of production (*WFP*), which is a key focus of our study. However, our $WFU_{\$}$ estimates should not be applied to individual power plants given the potential for substate variability in electricity prices.

We use estimates of consumptive water use in hydroelectricity generation from Grubert (2016). Grubert (2016) estimates evaporation associated with each hydroelectricity generation reservoir. Further, this study provides water consumption per unit energy produced (m^3/GJ) for 20 different regions within the United States. There are several critical assumptions made by Grubert (2016), namely the allocation of storage space and evaporation among multipurpose reservoirs, that lead to significant uncertainty, especially when evaluating individual reservoirs. For this reason, we only report national *WFP* for hydropower production.

2.7. Water Footprints of Mining Production

Water is used to quarry minerals and ores, as well as for crushing, screening, washing, and dust suppression. We include water injected into the ground to extract crude petroleum and natural gas as a mining use of water. In addition to withdrawing and consuming water, mining operations can also "produce" water by dewatering mines or as a by-product of oil and gas extraction. This water is not included in our analysis unless it is used for a beneficial purpose in the mining operation, such as re-injection or dust suppression. Note that the water used to transport or process raw minerals, ores, petroleum, or natural gas is not included here.

We estimate *WFP* for mining from surface and groundwater sources. To do this, we utilize water withdrawal data from Maupin et al. (2014) and consumption coefficients from Solley et al. (1998). Due to limited extraction data for many of the materials, we are unable to calculate the water footprint of specific mined items, such as minerals, ores, natural gas, or oil. Instead, we multiply consumptive water use coefficients by total mining withdrawals from Maupin et al. (2014) to estimate the *WFP* of the entire mining industry within each county.

There is uncertainty in estimates of mining water withdrawals and consumption since very few mining operations track and report their water usage. Moreover, mining water usage can be highly variable depending on mining technique, climate, and available water supplies. Therefore, our approach presents a first-order approximation. Additional data on material and site-specific water consumption would improve our understanding of how water is used within the mining industry.

Through a review of the literature, we estimate *WFU* for 15 mined products (see Table 2 for a list of references). Note that we give preference to studies based in the United States, but also incorporate international studies, due to limited U.S. research in mining water use. For all mined products, we quantify median $WFU_{\$}$ values ($m^3/\$$) of sales. Note that we provide estimate of water consumption per ton of production (m^3/ton) in our final database, as well water consumption per energy potential (m^3/TJ) for energy materials, such as coal, natural gas, crude oil, and uranium. Prices of all minerals and ores are for 2012 and are taken from USGS (U.S. Geological Survey, 2017), while energy products come from the EIA (EIA, 2013a, 2013b 2017b, 2017c).

2.8. Input-Output Methods to Determine Indirect Water Footprints

An economic input-output (IO) matrix can be paired with our estimates of direct $WFU_{\$}$ to calculate the direct and indirect water footprint of each sector. An IO table represents interdependencies between industries by showing intersectoral input purchases required to produce output in each sector. For instance, leather manufacturing requires purchases from the cattle industry, which requires feed purchases from the grain industry, who in turn purchases from the fertilizer industry and so on. The total direct and indirect water requirements throughout a product's supply chain can be calculated using an environmentally extended version of the Leontief IO model:

$$w = k(I - A)^{-1} y \tag{9}$$

where w is a vector of industry direct and indirect water consumption (m^3) due to the final demand of y goods ($; U.S. Census Bureau, 2017). Direct water consumption is water either purchased or self-supplied by sector j to produce its goods, while indirect water consumption is water used in sector i production whose products are input to sector j output. k (m^3/$) is a row vector of direct water footprints per dollar of output for each industry (i.e., $WFU_\$$). In the IO literature, the k vector of $WFU_\$$ values determined in this study is considered an environmental multiplier (e.g., Steen-Olsen et al., 2012). Finally, I is the identity matrix and A is the direct requirement matrix, which represents how much input from sector i is needed to produce one unit of output in sector j. Total requirements, $(I - A)^{-1}$, which represent total industry inputs (direct and indirect) to deliver one dollar of industry output to final users, were taken from U.S. Bureau of Economic Analysis (2017).

3. Results

3.1. Water Footprints of U.S. Production

The total water footprint of economic production in the United States is 7.30×10^{11} m^3 per year. Of this, 6.03×10^{11} m^3 is from rainfall used to grow crops for food, feed, and fuel. Surface water (6.68×10^{10} m^3) and groundwater (6.11×10^{10} m^3) are valuable inputs in the production of irrigated agriculture, as well as every other economic sector. The volume of blue water used in national economic production is roughly 15 times less than the U.S. total average annual runoff (1.96×10^{12} m^3; USGS, 2017) and only two-thirds the national water supply and storage capacity (1.94×10^{11} m^3; U.S. Army Corps of Engineers, 2017). The entire consumption of blue water resources represents roughly one-third of withdrawals. These statistics suggest an abundance of national water resources. However, these lumped values mask localized water issues and stresses.

Crop production comprises the vast majority (95.4%) of total *WFP*. Green water comprises 86.5% of all consumptive crop water use, while surface and groundwater contribute 5.9% and 7.6%, respectively. Roughly 84% of U.S. harvested crop area is strictly rainfed, with most of this cropland dedicated to corn, soybeans, wheat, and hay and haylage, grown in the Midwest and High Plains. Corn grain and silage, hay and haylage, rice, wheat, soybeans, cotton, and almonds are among the largest irrigation users. Together, these seven crops are responsible for 75% of national groundwater consumption and 47% of national surface water consumption. Figure 1 shows the crops with the largest *WFP* by water source. Note the importance of rainfall on irrigated agricultural lands. Figure 2 maps crop water footprints by water source.

Noncrop economic sectors contribute 13.3% and 38.4% to ground and surface *WFP*, respectively. Figure 3 illustrates that most (1.59×10^{10} m^3, or 61.7%) of the annual noncrop surface *WFP* is due to evaporative losses from hydropower reservoirs and nonrevenue water losses in municipal distribution systems. As noted earlier, significant uncertainity exist in estimates of both sectors depending on what fraction of water losses is considered consumptive use and how water is allocated among multiple uses. Thermoelectric power generation, though the sector with the largest withdrawals, consumes the third most surface water and seventh most groundwater amongst noncrop sectors. This is because 97.5% of thermoelectric freshwater withdrawals correspond to power plants that employ once-through cooling systems, which typically consume only 1–3% of withdrawals. Figure 4 illustrates the *WFP* for thermoelectric power generation for each U.S. county. The direct water consumption for animal husbandry is 2.59×10^9 m^3 annually, with nearly half of all livestock water use occurring in the Great Plains and California (see Figure 5). Beef cattle are responsible for 56.0% of the water footprint of livestock production.

The *WFP* of manufacturing and service sectors is 2.82×10^9 m^3 and 2.32×10^9 m^3 per year, respectively. The manufacturing sector relies less on groundwater than service industries, with only 21.6% of its *WFP* coming from groundwater sources, compared to 37.2% from the service sector. The top five water consumers are primary metal manufacturing, food manufacturing, chemical manufacturing, wholesale trade, and food and beverage stores. Whereas the first three manufacturing sectors can attribute their large *WFP* primarily to their high $WFU_\$$, the two service sectors have modest $WFU_\$$ but their large *WFP* is due to the sheer size of their economic production within the U.S. economy.

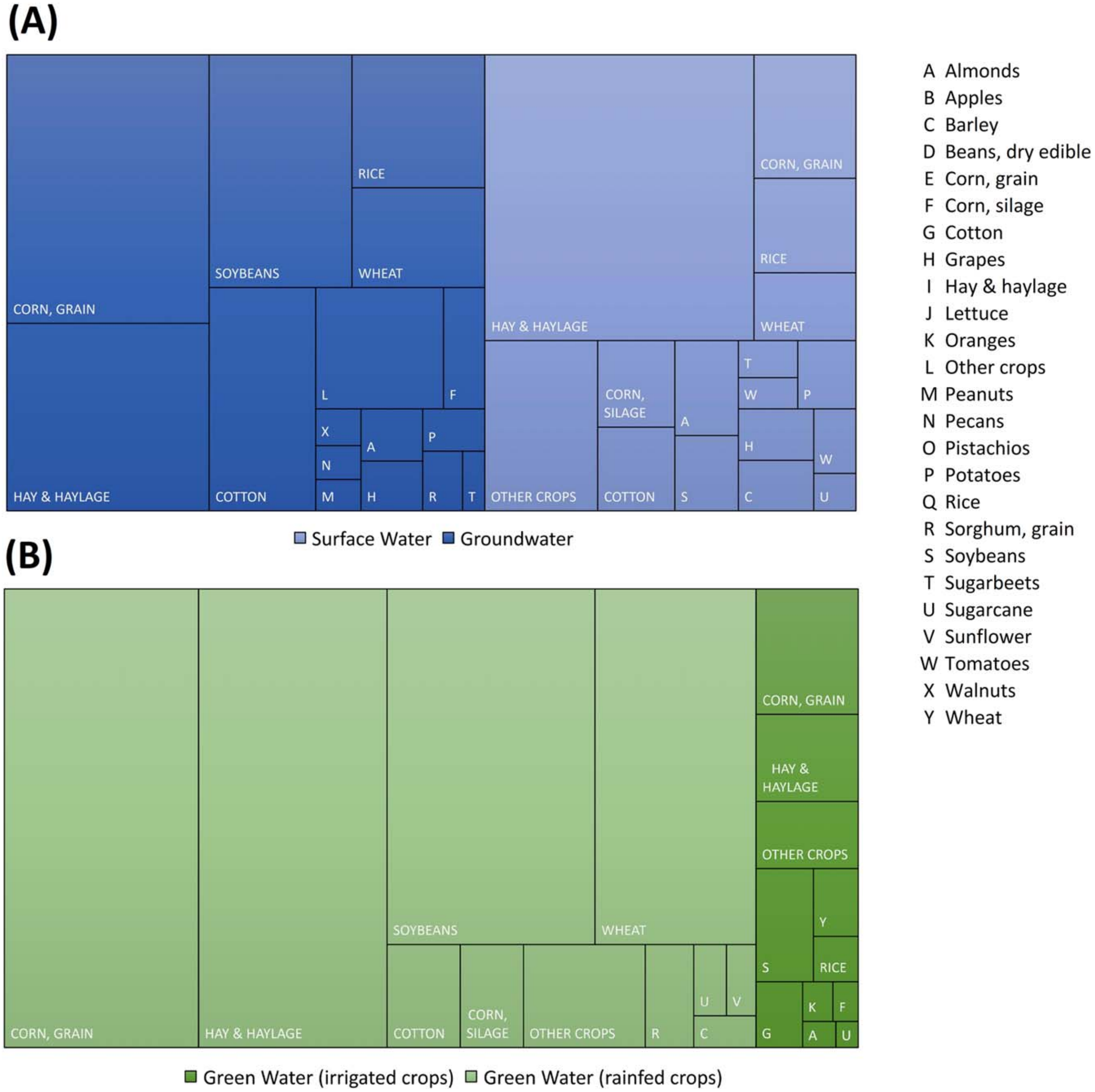

Figure 1. Relative contribution of each crop to the water footprint of crop production in the United States. (a) Surface and groundwater footprints of irrigated crops. (b) Green water consumed by irrigated and rainfed crops. Note that rainwater is important on irrigated croplands. Tiles are scaled relative to size within plot. Boxes cannot be compared between (a) and (b), since green water consumption is substantially larger than blue water consumption. Irrigated crop production in the United States consumes a total of 52.9 km^3 of groundwater, 41.1 km^3 of surface water, and 72.1 km^3 of green water. Rainfed crops require 530.8 km^3 of green water.

Figure 6 shows the spatial variation in *WFP* of the combined manufacturing and service sectors. Generally, states with larger manufacturing economies (primarily in the Rust Belt, the Southeast, Texas, and California) have the largest *WFP*. The cities with the largest footprints are Chicago, Los Angeles, and New Orleans. Laredo, Texas has the smallest manufacturing *WFP* of any city, largely since much of its publicly supplied water is from brackish groundwater that is not included in our estimates. We reiterate that our study accounts for inter-CFS Area water transfers, which we find account for 8% of all public supply water withdrawals. Therefore, our results represent where the water is actually used, not the point of diversion.

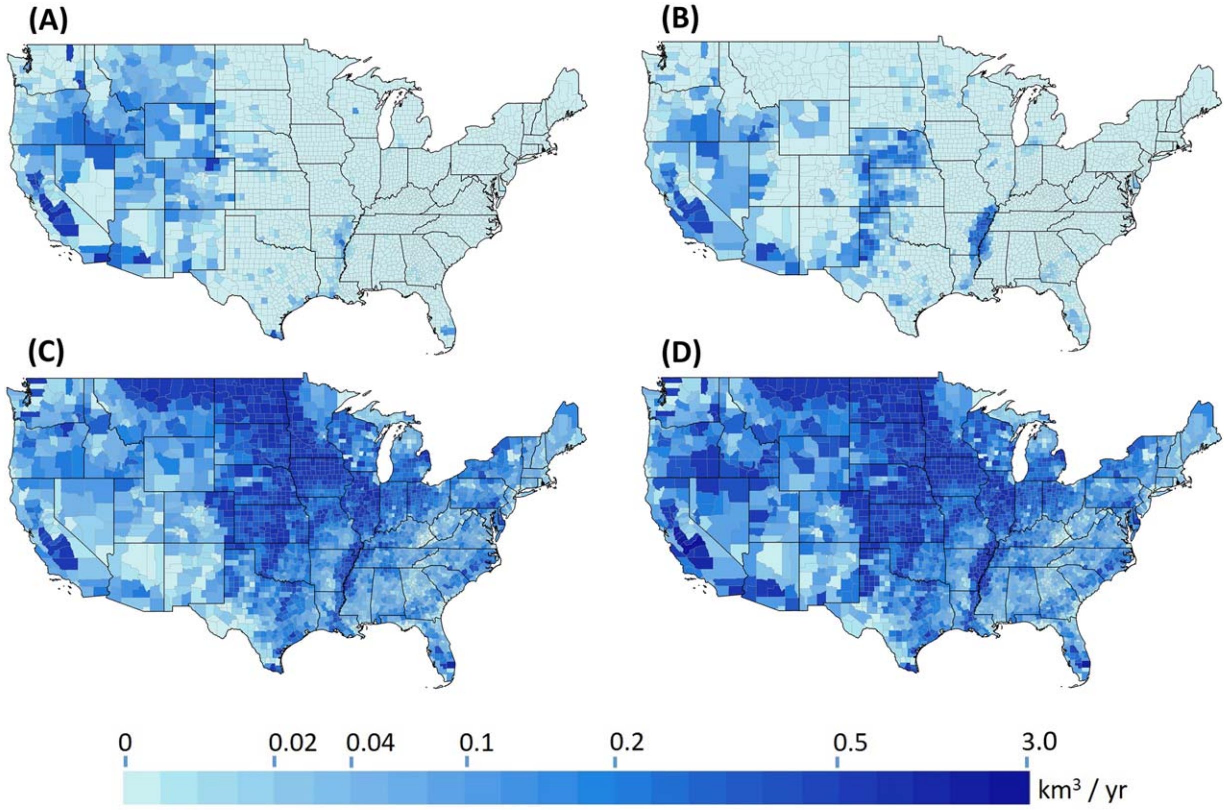

Figure 2. Maps of water footprints of production for the United States. (a) Surface water footprints, (b) groundwater footprints, (c) green water footprints, and (d) total water footprints of crop production (km^3/yr) at the county spatial resolution.

There is significant spatial variability in both total water consumption and sectoral water dependencies across the United States. Figure 7 reveals the sector with the largest blue *WFP* in each county. Eight of the ten counties with the largest *WFP* are in California, with irrigated agriculture as the leading water user in each. Ten percent of U.S. counties are responsible for 74% of national *WFP*. Clustering is evident in many places, such as cereal farming in the Midwest and High Plains, dairy farming in Wisconsin, New York, and Pennsylvania, fruit and nut farming in California and Florida, and other livestock production (namely, pigs) in Iowa and North Carolina. Some regions of the country disproportionately provide water to key economic sectors. For instance, the *WFP* of service providing industries is heavily concentrated in urban areas, particularly in the Northeast. The service sector ranks ninth (out of thirteen) in terms of total *WFP*, but has the fourth highest number of counties where it is the dominate water consumer. Alternatively, the oilseed, vegetable, and nut sectors are significant water consumers nationally (ranked third, fourth, and fifth in total *WFP*, respectively), yet water use of these sectors is largely concentrated in a relatively small number of counties (each less than 2% of all counties).

3.2. Water Footprints per Unit of Production

We calculated the *WFU* for 133 crops, 8 livestock animals, 378 commercial, industrial, and institutional sectors (CII), 15 mined resources, thermoelectric power generation (by 5 fuel types and 2 circulation types), and aquaculture. Together, this comprises the most comprehensive estimation of *WFU* in the literature to date. Moreover, most *WFU* values were calculated for subnational spatial units. This spatial differentiation enables us to calculate a range in *WFU* values which can be used to benchmark economic sectors and products. Water consumption was normalized by U.S. dollars ($WFU_{\$}$), production tonnage ($WFU_{ton}$) and/or energy WFU_{TJ}.

Over 50,000 unique $WFU_{\$}$ were calculated for different industries and products across the nation. In Figure 8, we show statistics on blue $WFU_{\$}$ after grouping them into broader sectoral categories. Most agricultural sectors have $WFU_{\$}$ greater than the national average, representing both low-value water uses and high

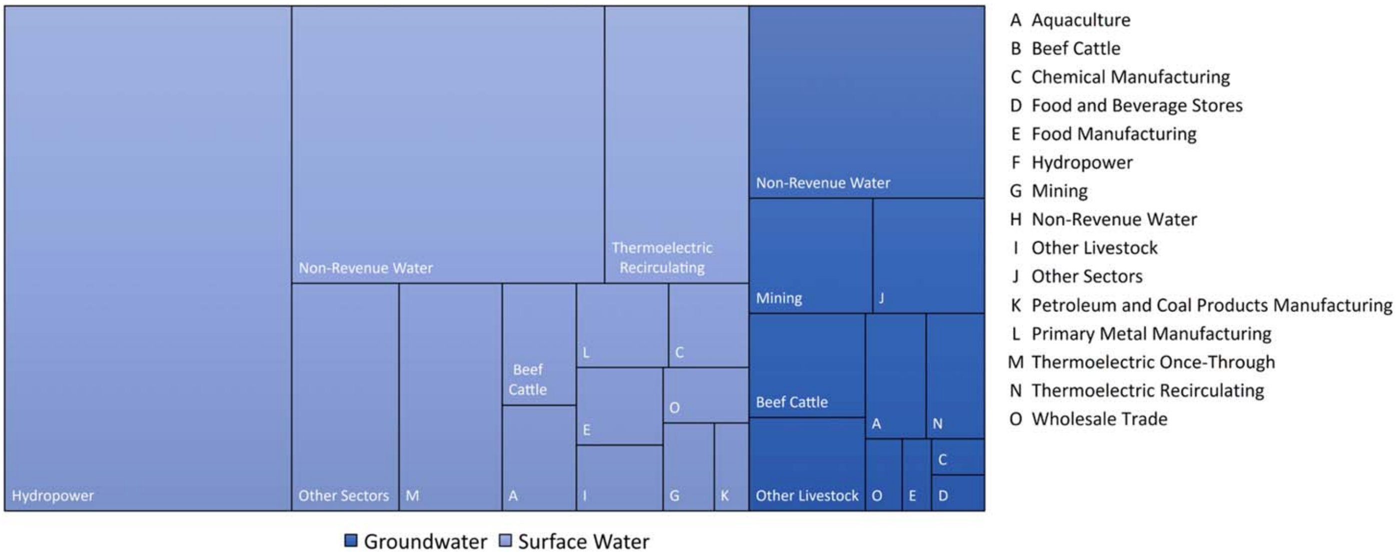

Figure 3. Relative contribution of each noncrop sector to the collective U.S. water footprint of these sectors. Contribution by water source is provided. Tiles are scaled relative to size. Noncrop sectors utilized a total of 8.1 km^3 of groundwater and 25.6 km^3 of surface water in their production processes.

usage of water. Generally, $WFU_\$$of manufacturing and service providing industries are several orders of magnitude less than the national average $WFU_\$$. New York City and Boston have the smallest CII $WFU_\$$ due to their focus on high value service industries, while New Orleans and West Virginia have the two largest $WFU_\$$ since their economies rely more on water-intensive heavy industries.

There is significant variability within each sectoral category due to production differences between individual products or industries within a sector, spatial differences in water utilization intensities, and different production efficiencies within the same industry. The greatest variability in $WFU_\$$ is within the crop sectors. This variability is due to local climate differences, management decisions (e.g., planting and harvesting dates, irrigation practices, etc.), and differences in water requirements by crop type. Although not represented in Figure 8, crop farming sectors also utilize green water to meet its direct water requirement. In some locations and for certain crops, irrigation water (i.e., blue water) is not applied, as the crop is strictly rainfed.

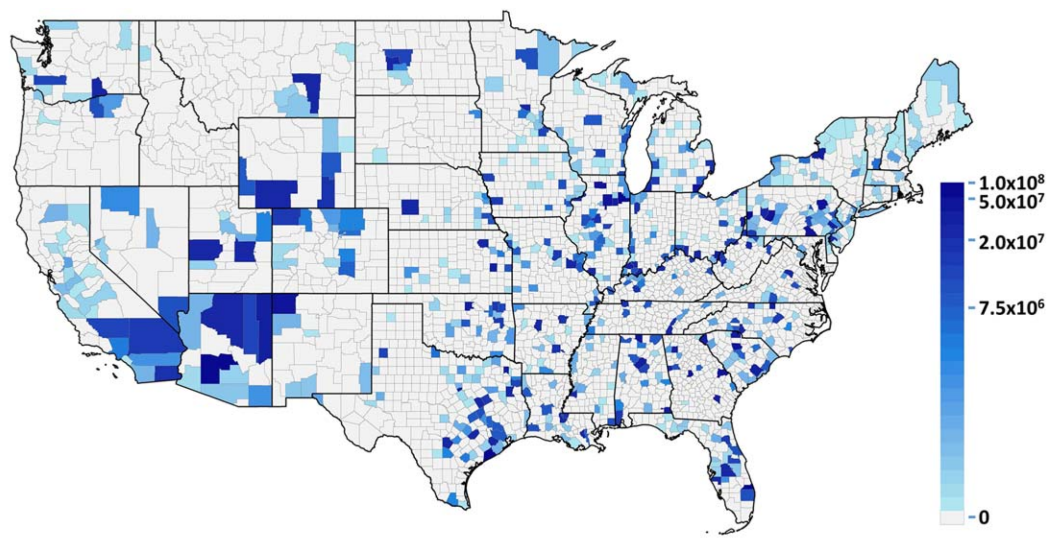

Figure 4. Blue water footprints of thermoelectric power generation (m^3/yr) for the county spatial scale the United States.

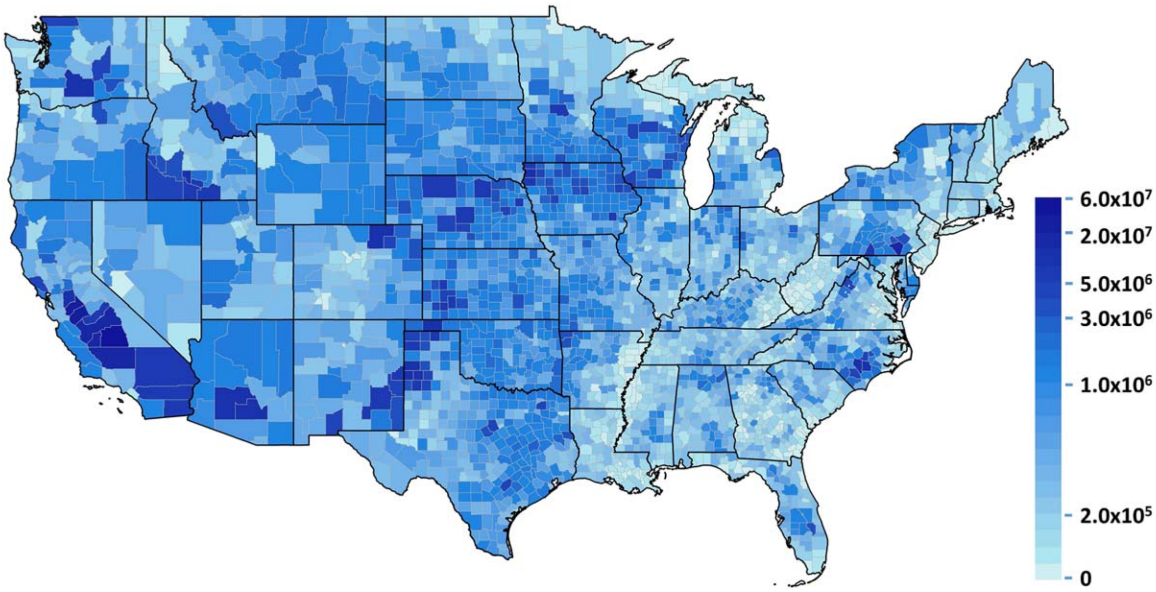

Figure 5. Blue water footprints of livestock production (m^3/yr) for the county spatial scale in the United States.

3.3. Direct and Indirect Water Footprints

Previous studies have found that 93% of U.S. economic sectors use more water indirectly than they use directly (Blackhurst et al., 2010). We too find that, on average, 93% of sectors use more water through their supply chains than they consume directly. However, these statistics provide a national average value and therefore disguise significant water use variability within each sector. For instance, if all sectors sourced their inputs from companies who are among the top 25% most efficient water users in their industry, only 72% of sectors would use more water indirectly than directly. Alternatively, if all sectors were supplied by the least efficient water users (bottom quartile), 99% would depend more on indirect than direct sources of water (see supporting information Figure S3).

The fact that we calculate variability in $WFU_\$$ for each sector enables us to determine opportunities to conserve water. While companies may aim to reduce their water footprint through improved water efficiencies in their own production processes, we find that greater water savings can often be achieved by procuring production inputs from more water efficient suppliers. In fact, 94% of industries could save more water by sourcing from the most efficient water users than they could by converting their own operations to be among the most efficient water users within their industry. Moreover, 87% of industries potential indirect water *savings* exceed their total direct water use.

Sugar refining is one example of an industry that consumes more water indirectly than directly. Table 3 provides an example of the direct and indirect blue water footprint of $1,000 in "sugar and confectionery product manufacturing" production. Additionally, Table 3 shows the direct and indirect $WFU_\$$ for a 5 lb (2.27 kg) bag of sugar. This example mirrors that of Blackhurst et al. (2010), but we now demonstrate how national average water use coefficients mask significant variability in water use across the country. We compare model outputs using the national average, high, and low $WFU_\$$ estimates. The high and low $WFU_\$$ assumes each sector sources its inputs from the most inefficient and efficient blue water users, respectively. The example in Table 3 shows that total water consumption associated with the national average $WFU_\$$ is roughly 37 times larger than if the sugar industry sourced its inputs from the most efficient water users. Alternatively, if the sugar industry sourced from the most inefficient water users, it would consume 10 times more water through its supply chain.

Direct water use by the sugar manufacturing industry is a small contributor to its overall $WFU_\$$. The largest determinant of the $WFU_\$$ of sugar is the amount of irrigation water resources used to grow sugar cane and sugar beets. Whether these crops are primarily rainfed (as the case in the "Low" $WFU_\$$ case) or are heavily irrigated ("High" $WFU_\$$) can have dramatic implications on the total blue $WFU_\$$ of the sugar industry. In fact, agricultural products contribute only 35% of the sugar industry's total blue $WFU_\$$ in the "Low" scenario but

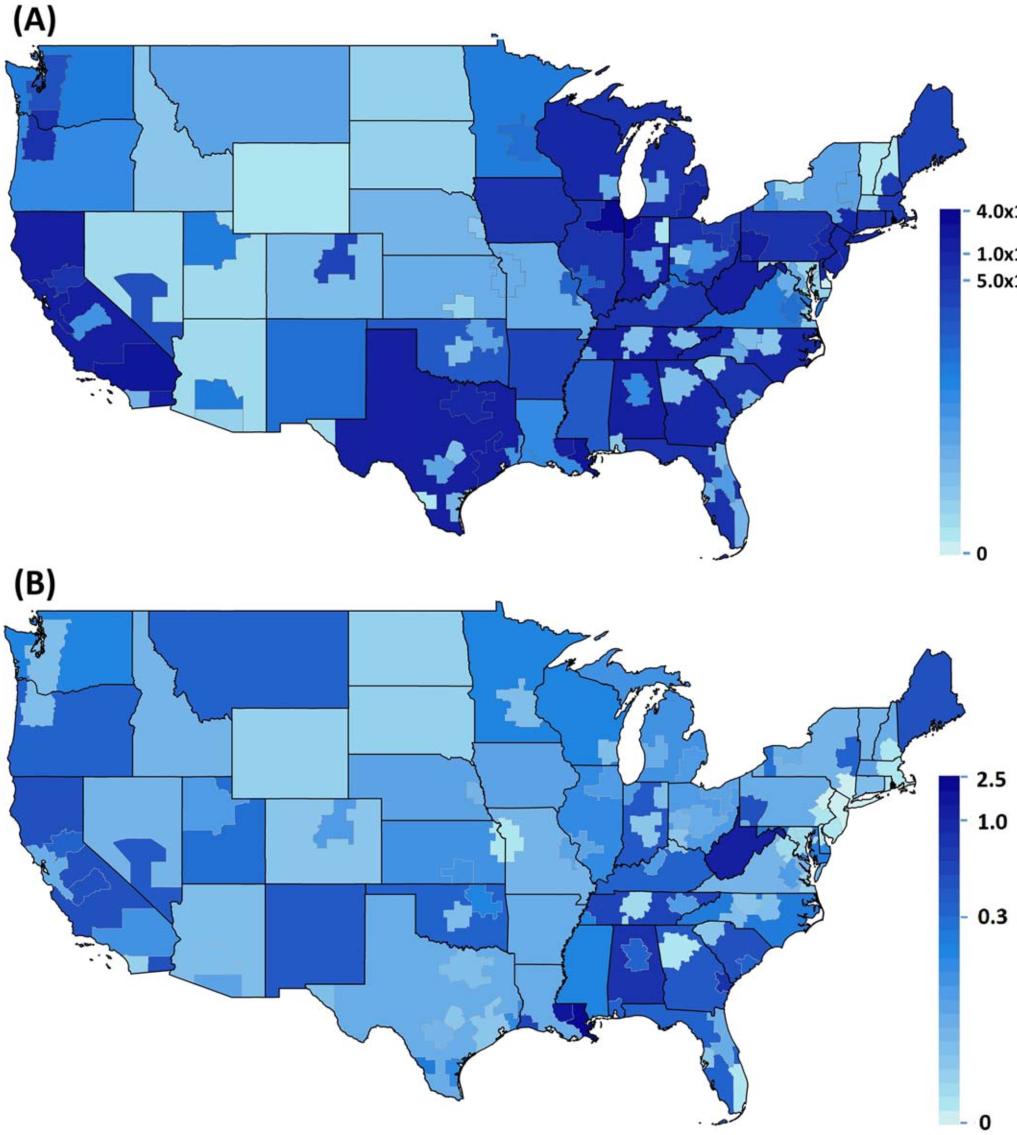

Figure 6. Blue water used in U.S. manufacturing and service sectors. (a) Water footprint of production (m^3/yr) and (b) water intensity (m^3/\$) of each CFS Area.

are responsible for over 99% of total water consumption in the "High" scenario, whose total blue $WFU_\$$ is over 3 orders of magnitude larger than the "Low" scenario. Water use attributed to other sectors can also differ by one to 2 orders of magnitude but the relative effect of these changes on the overall $WFU_\$$ is small. This example demonstrates the ability of our spatially and sectorally resolved water footprint estimates to benchmark possible water savings in the U.S. economy. While this case illustrates the potential for water savings within a product's supply chain, it should be noted that actual water savings are bounded by other factors such as production constraints of the most efficient water users, as well as economic considerations.

3.4. Validation and Uncertainty of Water Footprint Estimates

Water footprint assessments, including this one, are subject to considerable uncertainty. To date, only a few studies (e.g., Zhuo et al., 2014) have conducted a rigorous uncertainty analysis of water footprint estimates. Others have determined the sensitivity of their water footprint estimates to input parameters (Grubert, 2016; Mayer et al., 2016; Tuninetti et al., 2015; Wang & Zimmerman, 2016). A lack of water metering and insufficient data availability make it challenging to validate the findings of our study. Nonetheless, we compare our results with other estimates in the literature, albeit at coarser spatial or sectoral resolutions, to

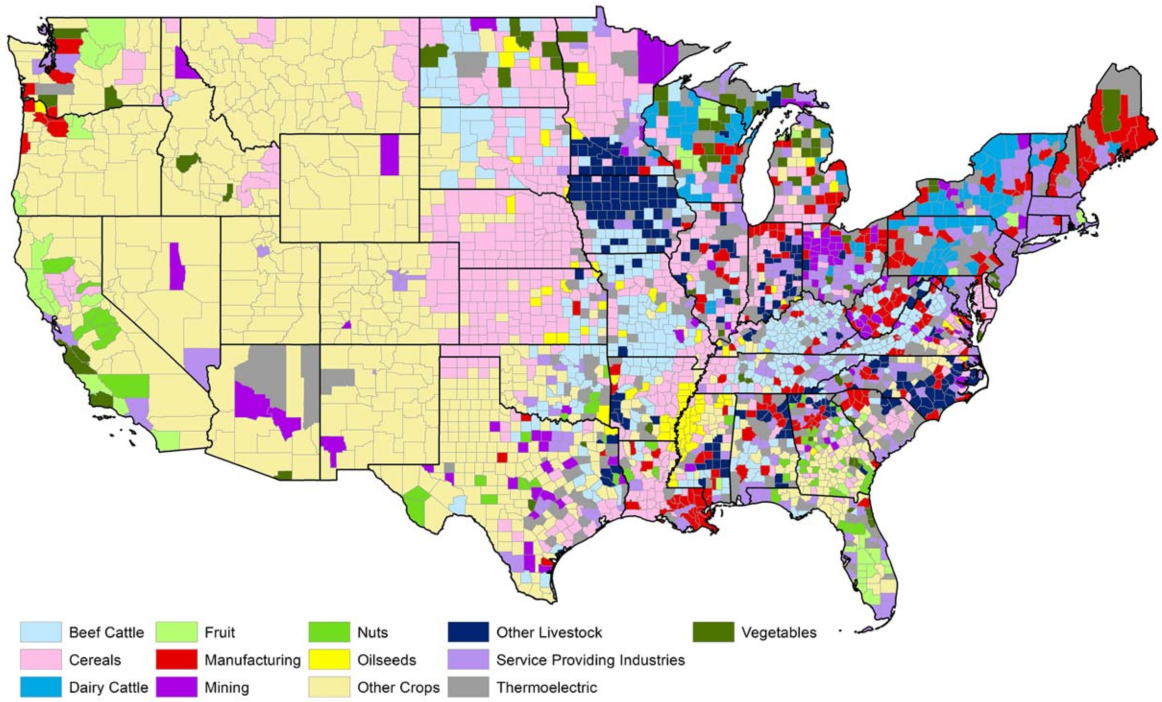

Figure 7. Sector with the largest blue water footprint in each U.S. county. Agriculture is the largest water user in 2,164 of the 3,143 counties. In other counties, service industries (354), thermoelectric power generation (289), manufacturing (234), and mining (102) are the dominant water users. Note that hydropower, aquaculture, and nonrevenue water uses are not included in the ranking since county level data are not available for these water uses. The CFS Area average $WFU_\$$ for service and manufacturing sectors was multiplied by county economic production to estimate their *WFP*.

determine the reasonableness of our results. We expect our findings to be similar to other studies, but do not necessarily require a precise match in values, due to the differences in time periods, definitions of sectors, and methods between studies.

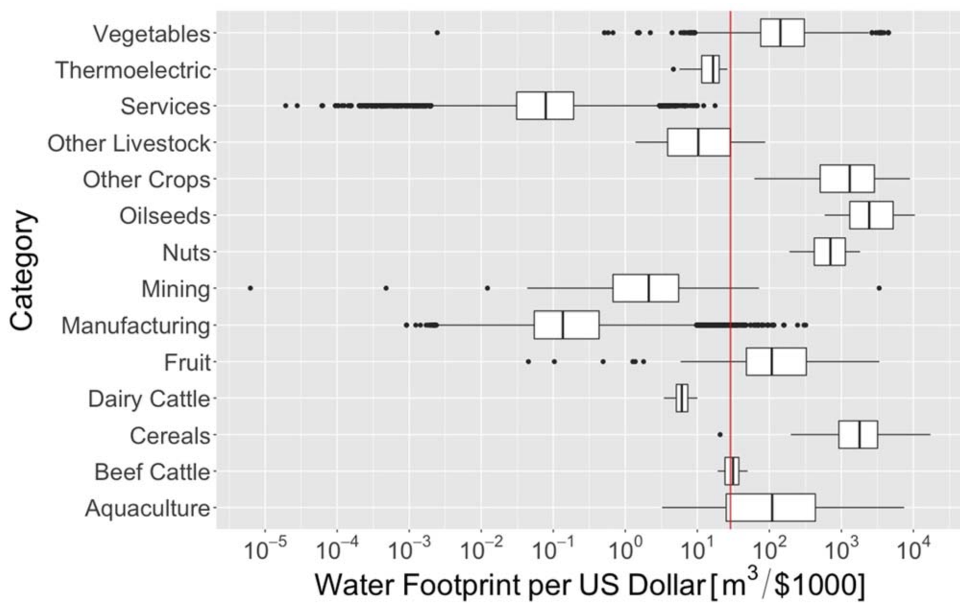

Figure 8. Statistics of blue water footprint per unit (m^3/$1,000) by broad sectoral categories. The median, 25th and 75th percentiles are represented by the box plot, while the whiskers extend from each hinge 1.5 times the interquantile range. Outliers are denoted as individual points. The vertical red line represents the average water footprint per U.S. dollar of the U.S. economy (i.e., total water use divided by total production). Figure is graphed using ggplot2 R package from Wickham (2009).

Table 3
The Direct and Indirect Blue Water Footprint of the "Sugar and Confectionery Product Manufacturing" Sector

	m^3/$1,000			Liters/1 kg bag		
Sector Name	Low	National average	High	Low	National average	High
Direct water use						
Sugar and confectionery product manufacturing	0.61	1.44	3.25	0.29	0.68	1.53
Indirect Water Uses						
Sugar cane and sugar beets farming	0.30	37.35	412.99	0.14	17.60	194.62
Oilseed farming	0.02	3.75	61.45	0.01	1.76	28.96
Grain farming	0.00	3.56	22.12	0.00	1.68	10.42
Electric power generation, transmission, and distribution	0.01	0.29	0.51	0.00	0.13	0.24
Paperboard container manufacturing	0.02	0.07	0.14	0.01	0.03	0.07
Fertilizer manufacturing	0.01	0.03	0.03	0.00	0.02	0.02
All other indirect uses	0.59	11.43	79.01	0.28	5.38	37.23
Total, all sectors	1.55	57.91	579.51	0.73	27.29	273.09

Note. $0.47/ kg.; World Bank (2017).

We convert studies that present crop water withdrawals to consumptive water use values for comparison. We convert withdrawals presented by Maupin et al. (2014) and applied water given by USDA (2014c) to consumptive values using irrigation efficiencies suggested by USDA and USGS (Dickens et al., 2011; Howell, 2003). Coefficients suggested by FAO (Brouwer et al., 1989) were used to account for conveyance losses. For each location, we determine an average consumptive use coefficient by taking the weighted average irrigation efficiency with the fraction of cropland employing each irrigation technology acting as the weight. The crop area utilizing each irrigation method comes from government data (Maupin et al., 2014; USDA, 2014c).

Supporting information Figure S4 shows that our results compare favorably with previous water footprint studies and government reports on water use within the United States. At the national level, our estimates of crop green, surface, and groundwater footprints are within the range of estimates in the literature and government reports. At the state-level, there is greater variability between our results and Maupin et al. (2014) and USDA (2014c) (see supporting information Figure S2). However, discrepancies between Maupin et al. (2014) and USDA (2014c) are actually greater than they are with our study. Variances in water use estimates are likely due to differences in study years and methodology. For example, we use long-term average crop water requirements (Mekonnen & Hoekstra, 2011a), whereas USDA (2014c) is for 2013 and Maupin et al. (2014) uses a variety of techniques to estimate water withdrawals which differ by state and utilize data from various years (Dickens et al., 2011).

In addition to comparing our results to existing estimates in supporting information Figure S4, we perform a sensitivity analysis on key parameters to capture some of the uncertainty within our results. A recent study by Zhuo et al. (2014) allows us to approximate the uncertainty in our total crop water footprint estimates. Using the same crop water model as we utilize in this study, Zhuo et al. (2014) found that the average uncertainty in crop water footprints was $\pm$30% (at 95% confidence level). Two-thirds of the uncertainty was due to uncertainty in precipitation and reference ET estimates. It is important to note, however, that their study covers fewer crops and is not specific to the United States.

There is less information available with which to compare our estimates for noncrop sectors, as shown in supporting information Figure S4. For this reason, we perform a thorough sensitivity analysis to key parameters and assumptions used in our estimates. We determine upper and lower bounds of *WFP* by adjusting model parameters and inputs within plausible ranges. Figure 9 illustrates the sensitivity of the *WFP* of noncrop sectors to critical parameters and assumptions. High and low *WFP* estimates of mining, manufacturing, and service providing industries were calculated by varying the consumption coefficient of each industry. Our results are particularly sensitive to consumptive use coefficients, which, in turn, are highly variable and uncertain (Shaffer & Runkle, 2007). Following Mayer et al. (2016), we use the consumptive coefficients representing the first and third quartile of coefficient values as our upper and lower bounds. We also varied nonrevenue water by $\pm$20% based on the average interannual variability seen in those cities for which we collected records for multiple years (shown in Figure 9). The sensitivity bounds shown in Figure 9 are a

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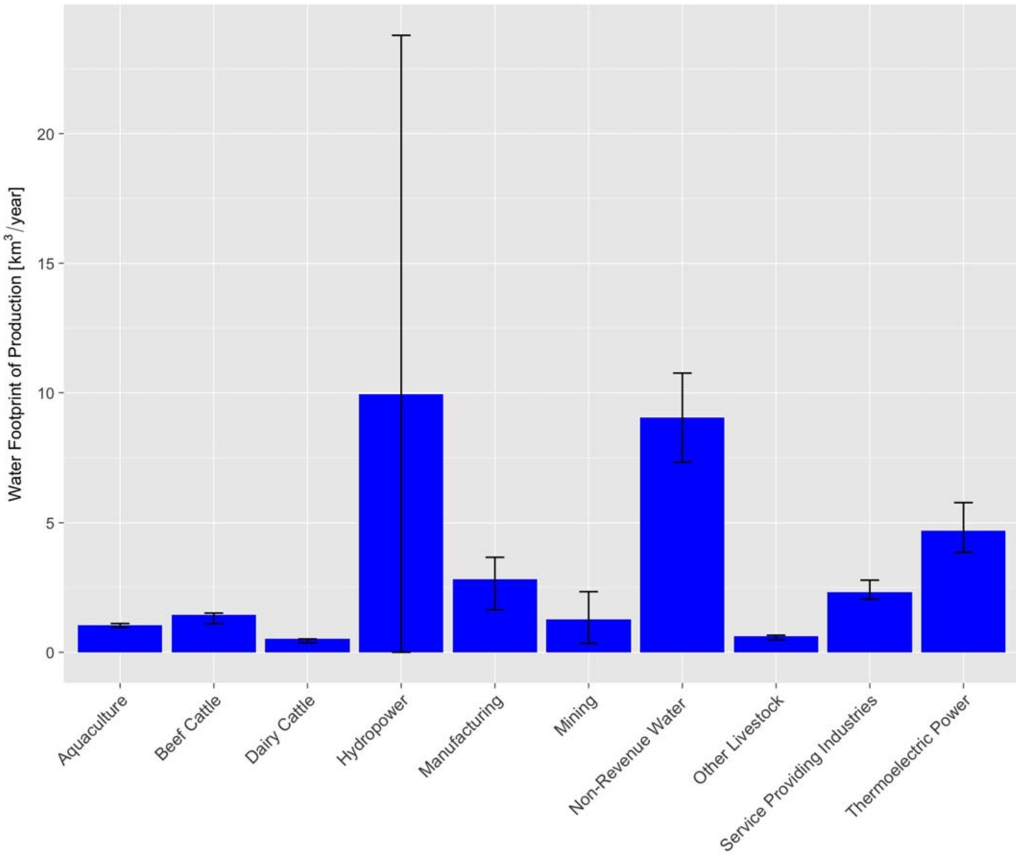

Figure 9. Blue water footprint of production (km^3/yr) for noncrop sectors in the United States. Error bars represent sensitivity to changes in key parameters or assumptions.

combination of changes in both consumption coefficients and nonrevenue water fractions (the latter is only applicable to industries utilizing publicly supplied water).

For all livestock sectors, we calculate low and high *WFP* by adjusting the animal water-use coefficients of each state to match the first and third quartile coefficients nationwide. Similarly, aquaculture *WFP* is bounded by high and low estimates of open water evaporation for each state of production (Farnsworth et al., 1982; Farnsworth & Thompson, 1982). Hydropower *WFP* estimates are most sensitive to how water consumption is allocated among the users of multipurpose reservoirs. Hydropower bounds in Figure 9 are based on two approaches used in the literature to allocate reservoir evaporation among multiple users: (i) no water is allocated to hydropower or (ii) all water consumption is allocated to hydropower. Other methods based on economic valuation or equal weighting of all dam purposes will produce estimates that fall within the bounds we present. Variability in thermoelectric *WFP* comes directly from Diehl and Harris (2014).

3.5. The Water Footprint of Food and Energy Production

Water is a critical input in the production of food and energy throughout the United States. We find that the blue water footprint of food does not align with population, nor cropland (see Figure 10). Rather, there is a strong demarcation around the 97th meridian, which is where precipitation (P) equals potential evapotranspiration (PET). Nearly 80% of the blue water footprint of food production (both crop and livestock) and 90% of irrigation dam storage is west of the P = PET line. Conversely, 80% of the water footprint of thermoelectric energy generation occurs east of the 97th meridian. The eastern United States consumes about 70% more water per capita for thermoelectric power generation than western United States residents. Since food and energy products are ultimately for human consumption, this spatial mismatch between the FEW system and population demonstrate how people are supported by nonlocal food and energy production, water consumption, and infrastructure.

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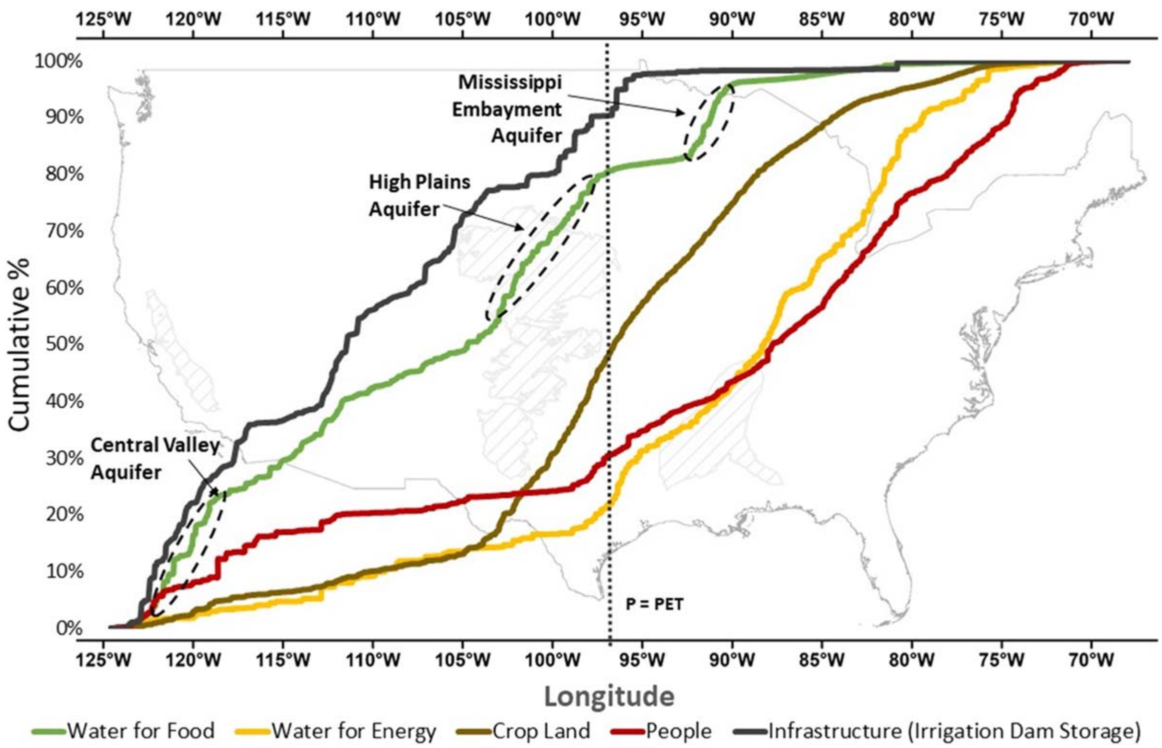

Figure 10. Cumulative blue water footprint of U.S. food and thermoelectric energy production moving from the western United States to the eastern United States. The P = PET line represents the approximate location where precipitation equals potential evapotranspiration. Note the sharp gradients in the water for food graph indicate the contribution of major aquifers: Central Valley, High Plains, and Mississippi Embayment. Please note the map of the United States is provided for longitude reference, along with the geographical position of the aquifers.

The importance of key groundwater aquifers for agricultural production is evident in Figure 10. In Figure 10 the sharp gains in the cumulative blue water footprint of agriculture correspond to the Central Valley, High Plains, and Mississippi Embayment aquifers. The gradient of blue water consumption sharply increases as farmers pump large volumes of water from these critical aquifer systems. In these locations, groundwater irrigation makes crop production possible and can serve as a buffer against drought and changing climates (Marston & Konar, 2017). Over two-thirds of aquifer depletion in the United States between 1900 and 2008 has occurred in these three aquifers (Konikow, 2013), which are critical to local economies, as well as domestic and international food security (Marston et al., 2015).

4. Conclusions

We quantified high-resolution water footprints of food, energy, services, manufacturing, and mining production in the United States. In doing so, we created the most detailed and comprehensive water footprint assessment of any country to date. We showed that the U.S. economy directly utilizes 7.30×10^{11} m^3 water each year to produce goods and services. This is equivalent to over one and a half times the volume of Lake Erie, America's fifth largest fresh water lake. The majority (83%) of the water footprint of U.S. production is from rainwater supplies, which supports farming. This finding reiterates recent calls in the literature to value rainfall as an important national resource (Falkenmark & Rockström, 2004). Optimal use of rainfall supplies through efficiencies in rainfed agriculture can lead to greater crop production and conserve irrigation supplies for more economically productive uses (Davis et al., 2017; Marston & Cai, 2016). In areas of water scarcity, conserving and reallocating irrigation supplies to more valuable uses can be encouraged through institutional measures, such as water rights banking, options markets, and aquifer and river basin caps (Debaere et al., 2014; Hoekstra, 2014; Marston & Cai, 2016).

This paper demonstrates the significant variability in water footprints of production, between sectors and locations. Water footprints of production can differ by several orders of magnitude—even within a relatively

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narrow industry—depending on local conditions and industry supply chains. The high-resolution water footprints that we present here enable supply chain managers to determine opportunities to conserve water through their sourcing of materials from more efficient water users. While we have provided physical bounds for water use within the supply chain of a product, many other factors must be considered (i.e. cost, logistics, policy) that may constrain potential water savings.

Our results highlight high degrees of spatial clustering in the water footprints of production in some industries. This economic clustering likely arises in order to leverage local economies of scale, natural resources, and comparative advantages. Yet, this spatial clustering indicates that these industries and their supply chains may be more exposed to spatially correlated water-related shocks, such as droughts and floods. As U.S. water resources become more stressed in the future, policy makers, and planners may need to consider tradeoffs between efficient production and resilience to local and nonlocal supply chain shocks.

This study provides a comprehensive evaluation of water use in the U.S. economy and highlights the importance of improving the national data collection efforts that underpin this work. Here, we call for a national effort to collect, store, and freely disseminate water use data that is both high-quality and high-resolution. Existing U.S. government databases on water use would benefit from consistent and transparent methods on water use estimates. Going forward, it is important that the key parameters used to produce these estimates—the consumptive use coefficients—be measured for many locations and economic sectors in order to bound this critical term. Even better, government databases would be improved by presenting metered water use data rather than estimated water use. This study has made great strides in increasing our understanding of the spatial and sectoral detail of water footprints in the United States. The next step forward is to improve our understanding of the temporal dynamics of water use. It is particularly important to evaluate how water use changes in time so that we can better anticipate and understand how users will behave under changing conditions, such as during drought.

Appendix A: List of Acronyms, Symbols, and Key Terms

Table A1 describes all acronyms, symbols, and key terms in this paper.

Table A1
Description of All Acronyms, Symbols, and Key Terms in This Paper

Description/term	Symbol/abbreviation	Definition
Direct water consumption		Direct water consumption is water purchased from a water supplier or self-supplied and used as in input in the current production stage.
Indirect water consumption		Indirect water consumption is water used in sector *i* production whose products are input to sector *j* output (i.e., water consumed throughout the supply chain of a product).
Water withdrawal		Water pumped from groundwater sources or diverted from surface water sources for use. A portion of this water often returns to the source and is available for reuse.
Water consumption		The part of withdrawn water not available for immediate reuse because it is evaporated, transpired, consumed by humans or livestock, or incorporated into products or crops.
Blue water		Fresh water supplies from surface water and groundwater sources
Green water		Soil moisture from precipitation, used by plants via transpiration.
Self-supplied		Water obtained directly from a water source by the user, as opposed to water delivered by a public supply systems.
Public supply		Water withdrawn from the initial source and delivered to the end user by a water utility.
Direct requirement matrix	*A*	Represents how much input from sector *i* is needed to produce one unit of output in sector *j*.
Commodity flow survey areas	*CFS* Areas	The commodity flow survey is conducted every 5 years by the U.S. Census Bureau and tracks transfers of commodities within the United States between more than 100 geographical areas, denoted as *CFS* Areas.
Commercial, industrial, and institutional	*CII*	Related to commercial activities, goods manufacturing or processing, or providing of services.
CII deliveries	*CIID*	Water deliveries to commercial, industrial, and institutional users within a given *CFS* Area.
Domestic deliveries	*DOD*	Water deliveries to domestic users (domestic as defined by USGS).
	E	The number of employees within the given industry.
Environmentally extended input-output model	*EEIO*	An environmentally extended version of the Leontief Input-Output model.
Evapotranspiration	*ET*	
Food, energy, and water	*FEW*	
Identity matrix	*I*	

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Table A1. (continued)

Description/ term	Symbol/ abbreviation	Definition
Input-output	*IO*	An *IO* table represents interdependencies between industries by showing intersectoral input purchases required to produce output in each sector.
Industrial withdrawals	*IW*	The self-supplied water withdrawals of a specific industry.
	k	A row vector of direct water footprints per dollar of output for each industry (i.e., $WFU_{\$}$).
	L	Length of time an animal utilizes water resource.
	m	The county or state where the water is utilized.
	n	Crop utilizing water.
	N	Number of animals.
Nonrevenue water	*NRW*	Water that is lost through real losses (e.g., leaks), apparent losses (e.g., theft or faulty metering), or authorized but unbilled water (e.g., street cleaning or fire-fighting). In fractional form, it represents the amount of total nonrevenue water divided by total public water supplies.
Net water transfers	*NWT*	Net transfers of physical water across *CFS* Areas boundaries (i.e., inter-*CFS* Area water transfers).
	o	Water source (i.e., green water, surface water, or groundwater).
Precipitation	*P*	
	p	Denotes whether the crop area is irrigated or strictly rainfed.
Potential evapotranspiration	*PET*	
Public supply withdrawals	*PS*	Water withdrawals by public water supply systems as reported by USGS.
	q	Livestock animal
	$S_{i,CFS}$	An industry-specific estimate of publicly supplied water deliveries for each *CFS* Area.
Secondary animal products	*SAP*	The total sales of secondary animal products, such as wool, milk, or eggs.
Slaughter price	*SP*	The slaughter price of the specified animal.
Total industrial withdrawals	*TIW*	The total industrial self-supplied water withdrawals within a *CFS* Area.
	w	A vector of industry direct and indirect water consumption (m^3) due to the final demand of *y* goods. Direct water consumption is water either purchased or self-supplied by sector *j* to produce its goods, while indirect water consumption is water used in sector *i* production whose products are input to sector *j* output.
Withdrawal coefficient	*WC*	Coefficient of water withdrawal or delivery per employee for industry *i*.
Water footprint of production	*WFP*	The volume of freshwater consumed during the denoted stage of production (m^3/yr). *WFP* can be further distinguished by water source (i.e., green, blue, surface, or groundwater).
Water footprint per unit of production	*WFU*	The volume of freshwater consumed during the denoted stage of production per unit of production (m^3/unit)
Water footprint per dollar of production	$WFU_{\$}$	The volume of freshwater consumed during the denoted stage of production per 2012 U.S. dollar of production (m^3/$)
Water footprint per terajoule of production	WFU_{TJ}	The volume of freshwater consumed during the denoted stage of production per terajoule (m^3/TJ)
Water footprint per ton of production	WFU_{ton}	The volume of freshwater consumed during the denoted stage of production per ton of production (m^3/ton)
Water purchases	$WP_{i,CFS}$	Water purchases from a public water supplier by a given sector *i* within a particular *CFS* Area
Water use coefficient	*WUC*	The daily water use volume per head of the specified animal.
	y	The final demand of goods within an input-output model.

Appendix B: Net Water Transfers Between CFS Areas

Table B1 list net water transfers between CFS Areas. Accounting for large water transfers between CFS Areas allows us to show the location where CII industries consume water. Water transfer data is not required to estimate WFP for crop production since our methodology does not rely on withdrawal data. For other industries or products it was assumed that the location of water withdrawals and consumptions were collocated.

Table B1
Net Water Transfers Between CFS Areas

Net water transfer [m^3/year]	Exporting CFS area	Importing CFS area	Reference
2.8E+05	Rest of AL	Atlanta, GA	Lawrence (2016)
1.2E+08	Rest of CO	New Mexico	McKean and Anderholm (2014)
3.2E+07	Orlando, FL	Rest of FL	Marella (2014)
2.8E+04	Rest of FL	Tampa, FL	Marella (2014)
2.3E+07	Miami, FL	Rest of FL	Marella (2014)
9.2E+03	Rest of GA	Atlanta, GA	Lawrence (2016)
3.5E+05	Atlanta, GA	Rest of GA	Lawrence (2016)

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Table B1. (continued)

Net water transfer [m^3/year]	Exporting CFS area	Importing CFS area	Reference
8.6E+06	Rest of GA	Rest of AL	Lawrence (2016)
1.5E+08	Washington DC (MD Part)	Washington DC (DC Part)	DC Water (2011)
4.0E+07	Omaha, NE	Rest of NE	C. Inbody of Nebraska Department of Natural Resources, personal communication, March 29, 2017.
7.8E+05	New York City (NJ Part)	Philadelphia (NJ Part)	New Jersey Department of Environmental Protection (2017); New Jersey Department of Environmental Protection Division of Water Supply and Geoscience and New Jersey Geological and Water Survey (2015); J. Shourds of New Jersey U.S. Geological Survey, personal communication, April 7, 2017.; S. Domber of New Jersey Department of Environmental Protection, personal communication, April 18, 2017.
1.6E+08	Albany, NY	New York City (NY Part)	New York City (2017); New York City Department of Environmental Protection (2017); Office of the Delaware River Master (2010) R. Kruzansky of New York State Department of Environmental Conservation Division of Water, personal communication, March 24, 2017. A. Bosch of New York City Department of Environmental Protection Bureau of Water Supply, personal communication, March 24, 2017.
7.9E+08	Rest of NY	New York City (NY Part)	New York City (2017); New York City Department of Environmental Protection (2017); Office of the Delaware River Master (2010) R. Kruzansky of New York State Department of Environmental Conservation Division of Water, personal communication, March 24, 2017. A. Bosch of New York City Department of Environmental Protection Bureau of Water Supply, personal communication, March 24, 2017.
1.4E+05	New York City (NY Part)	New York City (NJ Part)	S. Domber of New Jersey Department of Environmental Protection, personal communication, April 18, 2017.
1.4E+05	Rest of OH	Cleveland, OH	M. Hallfrisch of Ohio Department of Natural Resources Division of Water Resources, personal communication, January 25, 2017.
1.0E+06	Columbus, OH	Rest of OH	M. Hallfrisch of Ohio Department of Natural Resources Division of Water Resources, personal communication, January 25, 2017.
1.4E+06	Columbus, OH	Rest of OH	M. Hallfrisch of Ohio Department of Natural Resources Division of Water Resources, personal communication, January 25, 2017.
2.9E+07	Rest of OK	Oklahoma City, OK	City of Oklahoma City Utilities Department (2017) W. Andrews of U.S. Geological Survey Oklahoma Water Science Center, personal communication, April 25, 2017.
7.6E+07	Rest of OK	Tulsa, OK	City of Oklahoma City Utilities Department (2017) W. Andrews of U.S. Geological Survey Oklahoma Water Science Center, personal communication, April 25, 2017.
1.1E+07	Rest of TN	Rest of GA	Lawrence (2016)
6.9E+08	Rest of TX	Houston, TX	City of Houston Department of Public Works and Engineering (2017a,b)
2.8E+06	Austin, TX	Rest of TX	Texas Water Development Board (2017a,b)
6.9E+05	Beaumont, TX	Houston, TX	Texas Water Development Board (2017a,b)
7.2E+06	Beaumont, TX	Rest of TX	Texas Water Development Board (2017a,b)
7.8E+06	Beaumont, TX	Corpus Christi, TX	Texas Water Development Board (2017a,b)
9.9E+03	Dallas-Fort Worth, TX	San Antonio, TX	Texas Water Development Board (2017a,b)
4.8E+04	Dallas-Fort Worth, TX	Houston, TX	Texas Water Development Board (2017a,b)
5.5E+05	Dallas-Fort Worth, TX	Rest of TX	Texas Water Development Board (2017a,b)
5.0E+03	Houston, TX	San Antonio, TX	Texas Water Development Board (2017a,b)
4.6E+05	Houston, TX	Austin, TX	Texas Water Development Board (2017a,b)
4.3E+05	Houston, TX	Rest of TX	Texas Water Development Board (2017a,b)
2.1E+05	San Antonio, TX	Austin, TX	Texas Water Development Board (2017a,b)
1.7E+05	San Antonio, TX	Rest of TX	Texas Water Development Board (2017a,b)
4.9E+03	Rest of TX	Beaumont, TX	Texas Water Development Board (2017a,b)
1.5E+05	Rest of TX	Houston, TX	Texas Water Development Board (2017a,b)
8.2E+05	Rest of TX	Dallas-Fort Worth, TX	Texas Water Development Board (2017a,b)
2.5E+06	Rest of TX	Austin, TX	Texas Water Development Board (2017a,b)
1.2E+07	Rest of TX	San Antonio, TX	Texas Water Development Board (2017a,b)
6.9E+07	Rest of TX	Corpus Christi, TX	Texas Water Development Board (2017a,b)
3.6E+07	Rest of VA	Virginia Beach-Norfolk, VA	City of Virginia Beach Department of Public Utilities (2017)
3.3E+07	Richmond, VA	Virginia Beach-Norfolk, VA	City of Newport Department of Waterworks (2017); Lynch (1992)
2.2E+08	Washington DC (VA Part)	Washington DC (VA Part)	S. Miller of Fairfax Water, Virginia, personal communication, May 5, 2017.

Note. Water use is often recorded at the place of withdrawal (Maupin et al., 2014); this necessitates records of water transfers to connect the place of water withdrawal and location of the actual user. Water transfer volumes were not required for areas (e.g. California (California Department of Water Resources, 2013) and Colorado (Ivahnenko & Flynn, 2010)) that recorded water use at the place of demand.

Acknowledgments
The database of *WFP* and *WFU* created as part of this study is publicly available on WaterStat (http://waterfootprint.org/en/resources/water-footprint-statistics/). WaterStat is the most comprehensive water footprint database with publicly available data sets from peer-reviewed research based on the Global Water Footprint Assessment Standard. This material is based upon work supported by the National Science Foundation grant ACI-1639529 ("INFEWS/T1: Mesoscale Data Fusion to Map and Model the U.S. Food, Energy, and Water (FEW) System") and EAR-1534544 ("Hazards SEES: Understanding Cross-Scale Interactions of Trade and Food Policy to Improve Resilience to Drought Risk"). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. L.M. is thankful for support from the Department of Defense through the National Defense Science & Engineering Graduate Fellowship Program (32 CFR 168a).

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