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RESEARCH ARTICLE

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Drought Impacts to Water Footprints and Virtual Water Transfers of Counties of the United States

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Key Points:

- Virtual water content is larger in drought than non-drought across commodity groups, with the exception of feed
- Virtual water transfers are larger in non-drought than drought conditions, driven by larger commodity mass fluxes during non-drought
- Irrigation buffers production and transfers during drought

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Irrigation is increasingly important to agricultural production and supply chains in the United States. In this study, we seek to understand how irrigation (blue) water footprints of production are spatially distributed and how they differ in drought versus non-drought years. Similarly, we aim to understand the impact of drought on the irrigation virtually embedded in domestic supply chains and exports. To this end, we quantify the blue water footprints of agricultural products per unit mass produced (Virtual Water Content (VWC)) by surface, groundwater, and groundwater depletion sources, and then trace how this water is embedded in domestic agricultural commodity transfers and exports (Virtual Water Transfers (VWT)) for counties in a drought (2012) and non-drought (2017) year. Overall, we find that total VWC values are larger in drought than non-drought conditions across commodity groups, driven by surface water withdrawals. Conversely, VWT is larger in non-drought than drought, driven by larger commodity mass fluxes during non-drought. Our results highlight the importance of sustainably managing water resources so that they are available to mitigate the impact of future droughts on agricultural production and supply chains.

1. Introduction

The United States plays an important role in feeding the world as a major producer, consumer, and exporter of agricultural commodities (Ercsey-Ravasz et al., 2012; Konar et al., 2018; Xu et al., 2011). In the face of projected increases in water stress in the coming decades, prolonged droughts under climate change, and increasing variation in surface water (SW) availability (Devineni et al., 2015; Niraula et al., 2017; Smerdon, 2017), it is important to determine water-related risks to agricultural production and supply chains. Groundwater irrigation acts as a critical buffer to crop production (Troy et al., 2015) and supply chains (Marston & Konar, 2017), yet groundwater levels across many major aquifers supporting irrigated agriculture are in decline across the U.S. (Jasechko et al., 2024; C.-Y. Lin et al., 2024; Reidmiller et al., 2017), posing a potential future risk to production and supply chains. Surface Water Withdrawals (SWW) for irrigation also increased over the twentieth century, but have leveled off in the last several decades (Debaere & Kurzendoerfer, 2017; Ruess et al., 2022). The goal of this study is to determine how drought impacts the irrigation (blue) Virtual Water Content (VWC) (consumptive water use per unit mass produced) of different crop groups in the Conterminous United States (CONUS), as well as how drought impacts the irrigation embedded in domestic supply chains in the form of Virtual Water Transfers (VWT) (volume of water virtually embedded in commodity supply chains and trade) at a high-resolution county spatial scale.

Globally, agriculture is responsible for 70% of freshwater withdrawals and 90% of freshwater consumption (Gleick & Palaniappan, 2010; Marston et al., 2018; Postel et al., 1996; Vorosmarty et al., 2000). Within the United States specifically, irrigated agriculture is more productive both physically and economically, meaning that more mass and value are generated per unit area than rainfed agriculture (Lehrsch et al., 2014; USDA, 2022). Groundwater is an increasingly important source of water supplies for irrigation (Jasechko et al., 2024; C.-Y. Lin et al., 2024), especially in times of drought (Marston & Konar, 2017). In the last several decades groundwater use within several key aquifers the U.S. has been physically unsustainable (Famiglietti & Rodell, 2013; Gleeson et al., 2012), occurring at a withdrawal rate that exceeds natural recharge, consequently leading to groundwater depletion (Konikow, 2013). The United States is one of the largest users of groundwater for irrigated agriculture (Esnault et al., 2014; Wagner, 2017), contributing to it being a major exporter of groundwater depletion virtually embedded in its exports (Dalin et al., 2017).

Thus, groundwater withdrawals not only support agricultural production, but they are embedded in the domestic transfers and international exports of the United States. Large volumes of groundwater depletion (GWD) are embedded in the national agricultural supply chain of the United States, as well as in its international exports (Gumidyala et al., 2020). In 2002, 26.3 km^3 of nonrenewable groundwater was transferred domestically in the U. S. and 2.7 km^3 was sent abroad (Gumidyala et al., 2020). In 2012, 34.8 km^3 was transferred domestically and 3.7 km^3 was exported (Gumidyala et al., 2020). In other words, there was a 32% increase in domestic transfers and 38% increase in international exports of virtual groundwater depletion. However, the mass transfer reliant on groundwater depletion decreased over the same time period, although the value of goods reliant on groundwater depletion increased by 54%. Groundwater depletion embedded in agricultural supply chains represents its exposure to unsustainable water use, which is a future risk as the mass and value of agricultural commodities produced with unsustainable groundwater will eventually need to be replaced with production from elsewhere (Gumidyala et al., 2020). In this paper, we build on research by Gumidyala et al. (2020), but explicitly evaluate the impact of drought on groundwater depletion embedded in the transfers and exports of the U.S.

The impact of drought on VWC and VWT in the Central Valley of California has been evaluated (Marston & Konar, 2017). Despite a reduction in harvested area, the water footprint of agricultural production in the Central Valley increased over the course of the drought, because of larger crop water requirements with higher temperatures, as well as a shift to more water-intensive orchard and vine crops. The shift to more water-intensive crops during a drought seems counterintuitive at first, but this is because farmers adapted their production decisions in order to get more profit per unit of water applied, and orchard and vine crops are high value crops. Groundwater irrigation increased dramatically during the drought, buffering agricultural production and supply chains for distant consumers (Marston & Konar, 2017). However, the Central Valley of California is unique, because it has a diversity of agricultural production and conjunctive use irrigation systems. This begs the question about how VWC and VWT respond to drought throughout the rest of the CONUS. Here, we build on the research by Marston and Konar (2017) by determining the impact of drought on the blue water embedded in the production and supply chains of the U.S.

In this study, we estimate VWC and VWT for nine unique combinations of three crop categories (cereal grains, produce, and animal feed) and three water sources (SW withdrawals, groundwater abstractions, and groundwater depletion) at the county spatial scale. We quantify and compare VWC and VWT during a drought year (2012) with a non-drought year (2017). To do this, we rely on three input data sets: USDA NASS QuickStats for crop production data (USDA, 2022), Irrigation Water Use (IWU) data from Ruess et al. (2022, 2025), and the Food Flow Model (FFM) data from Karakoc et al. (2022) for county-level food flow data. Our research is motivated by the following questions, all framed in the CONUS: 1. How is VWC spatially distributed?, 2. How does VWC compare between a drought and non-drought year?, 3. How is VWT spatially distributed?, 4. How does VWT compare between a drought and non-drought year?, and 5. How much VWT is exported versus transferred domestically? In answering these questions, we present a high-resolution assessment of VWC and VWT by water source, crop category, and county. All results are made publicly available with the paper.

2. Methods

First, we calculate VWC for all counties within the CONUS in 2012 and 2017 using agricultural production information from the USDA NASS database (USDA, 2022) and irrigation data from the IWU data set (Ruess et al., 2022, 2025). Second, we calculate VWT using the VWC values calculated in the first step coupled with county-level food trade information from the FFM data set (Karakoc et al., 2022). All acronyms, data sources, and parameters relevant to the study are summarized alongside a schematic representation of the methods in Table 1.

2.1. Data Sources

Census data is available at the county scale detailing production data for various crops (USDA, 2022). Where production data are unavailable we instead calculate it using published acres harvested or acres bearing data coupled with yield data, supplementing census data with survey data where necessary (USDA, 2022).

Freight Analysis Framework (FAF) data (ORNL, 2022) provides domestic and international trade information for the US. Karakoc et al. (2022) have downscaled this FAF data to county-scale resolution within the CONUS, enabling our higher-resolution analysis. More specifically, FFM downscales FAF data for the first seven Standard Classification of Transported Goods (SCTG) commodity groups (USDOT, 2022), of which we focus on three in

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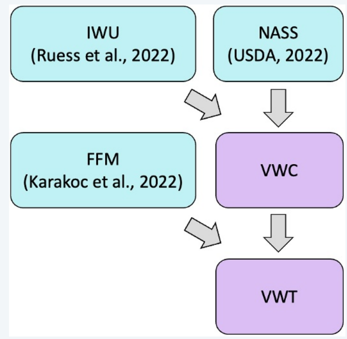
Table 1
Acronyms, Data Sources, and Parameters Relevant to This Study (Left), and a Schematic of the Methodology (Right)

Acronyms	
VWC	Virtual Water Content
VWT	Virtual Water Transfers
CONUS	Continental United States
Data Sources	
USDA NASS	National Agriculture Statistics Service (USDA, 2022)
FFM	Food Flow Model (Karakoc et al., 2022)
IWU	Irrigation Water Use (Ruess et al., 2024)
Parameters	
Spatial Resolution	County
Spatial Extent	CONUS
Temporal Resolution	Annual
Temporal Extent	2012 and 2017
Crop Categories	• Cereal Grains (SCTG 2) • Produce (SCTG 3) • Animal Feed (SCTG 4)
Irrigation Sources	• Surface Water Withdrawals (SWW) • Groundwater Abstractions (GWA) • Groundwater Depletion (GWD)

Flowchart



this work: cereal grains (SCTG 2); agricultural products except for animal feed, that is, produce including soybeans (SCTG 3); and animal feed and products of animal origin, that is, alfalfa/hay (SCTG 4).

Ruess et al. (2022) created the IWU data set, calculating county-scale crop-specific irrigation data for 20 unique crops and crop categories that all fall into one of the three crop categories defined above. This crop-specific irrigation data is further categorized by three water sources: SWW, groundwater abstractions (GWA), and groundwater depletion (GWD). Groundwater abstractions refer to all renewable and nonrenewable groundwater withdrawn for irrigation. Groundwater depletion refers solely to the portion of groundwater abstractions that are unsustainable, specifically the portion of groundwater abstractions that exceeded the aquifer's recharge capacity. In this study, we use the IWU data set from Ruess (2025), since it has greater spatial coverage than Ruess et al. (2022). Note that Ruess et al. (2022) is based on the annual CropScape Cropland Data Layer Boryan (2011) and should thus capture annual variations in area harvested between drought and non-drought years.

2.2. Gap Filling of USDA Production Data

Production data was collected from USDA NASS census reports (USDA, 2022) for each crop in each SCTG group. We prioritize the use of census data over survey data (where available) for two reasons: 1. Census data is more comprehensive and precise, and 2. Census data is available for most crops in 2012 and 2017. Due to the wide variety of census production units (tons, bushels, lb, CWT, etc.), all production units were converted to tons. A breakdown of unit conversions is available in Supporting Information S1.

For some crops, especially some fruits and vegetables, the census only reports acres harvested/bearing. Omitting these fruits and vegetables from the produce crop category would significantly under-represent true production. In these instances, we instead calculate production as the acres harvested or acres bearing multiplied by the yield. Census data for acres harvested/bearing is available at the county level (USDA, 2022), as is survey data for yield at varying spatial resolutions. We are confident in this methodology, as yield is a ratio (production divided by acreage) rather than an absolute value. Additionally, the commodities with limited information are generally grown in very few US counties and cover very limited acreage as compared to most other crops.

For crops with limited acreage or where more specific yield data was not available, we were forced to rely on national values. Additionally, some crops were omitted because yield and/or acreage data was only available for either 2012 or 2017, resulting in inconsistencies between our two study years. The omitted crops are: cranberries and boysenberries (2012 only); and beans, carrots, lettuce, melons, peas, and tomatoes (2017 only). Details describing data availability for all crops considered can be found in the Supporting Information S1.

Table 2
Crops and Crop Categories Included in This Study

Crop category	SCTG	Crops
Cereal grains	2	Barley, Corn, Millet, Oats, Rice, Rye, Sorghum, Wheat, and "Other SCTG 2"
Produce	3	Cotton, Peanuts, Potatoes, Pulses, Rapeseed, Soybeans, Sugar beets, Sunflower, Sweet Potatoes, and "Other SCTG 3"
Animal feed	4	"Other SCTG 4"

Note. Production and irrigation information by crop are used to determine Virtual Water Content (VWC) for individual crops. Virtual Water Transfers (VWT) are determined for the crop categories given by the Standard Classification of Transported Goods (SCTG) coding system to align with food flow information at this commodity resolution.

To protect small farms from being uniquely identifiable, USDA NASS (USDA, 2022) redacts data for many counties. To address these data gaps, we fill in redacted information using statistical allocations of larger-scale available data. More specifically, we filled redacted county values by evenly distributing the difference between the encompassing state's production value, and the sum of all reported (i.e., non-redacted) county values contained within the state. Importantly, we do not change counties where zero production is reported; these are left as zeros. This distribution methodology is reasonable because redacted counties generally have few producers and therefore very small production quantities.

After filling redacted counties for all unique crops, production data by crop were summed to obtain values by crop category following the groupings shown in Table 2. Figure 1 compares unfilled data retrieved directly from USDA NASS (USDA, 2022) to our filled versions for all three agricultural commodity groups.

2.3. Calculating Virtual Water Content

We calculate VWC [m^3/ton] based on irrigation and production data for each crop group as follows:

$$VWC_{o,c,w,y} = \frac{IWU_{o,c,w,y}}{P_{o,c,w,y}} \tag{1}$$

where IWU is irrigation water use (m^3), P is agricultural commodity production (ton), o is origin county, c is crop category, w is water source, and y is year. VWC can also be referred to as "crop water productivity" (Yang et al., 2006).

While we are ultimately interested in county values, we also calculate VWC at state and national scales for validation. Because VWC is a relationship between volume and mass, when calculating at the state and national scales we first spatially aggregate irrigation water and production values to these two larger spatial scales. We then calculate each VWC value individually (for all combinations of the three crop categories with the three water sources) as described in Equation 2, for all three spatial scales individually. To address outliers in the resultant VWC data sets (caused by large input data values), we winsorize all VWC values at the county and state scales using the 99.5% quantile to omit high values. We do not use a low value cutoff.

We also estimate VWC for 15 unique crops by irrigation withdrawal source (SW withdrawals, groundwater withdrawals, and groundwater depletion) in the CONUS in 2012 and 2017 by combining crop-specific irrigation withdrawal data with crop-specific production data. To generate these estimates, we repeat the same procedure used to produce the aggregate VWC estimates by dividing the crop-specific irrigation for a given water source by the crop-specific production tonnage for each county. The IWU data from Ruess et al. only contains crop-specific estimates for 17 crops, and aggregate crop group estimates for the remaining crops, in this case, "Other Produce," "Other Animal Feed," and "Other Pulses." Of these 17 specific crops, the USDA NASS agricultural census data provides county level production estimates for 15 of them. These crops are: barley, corn, cotton, millet, oats, peanuts, potatoes, rice, rye, sorghum, soybeans, sugar beets, sunflower, sweet potatoes, and wheat. We combine

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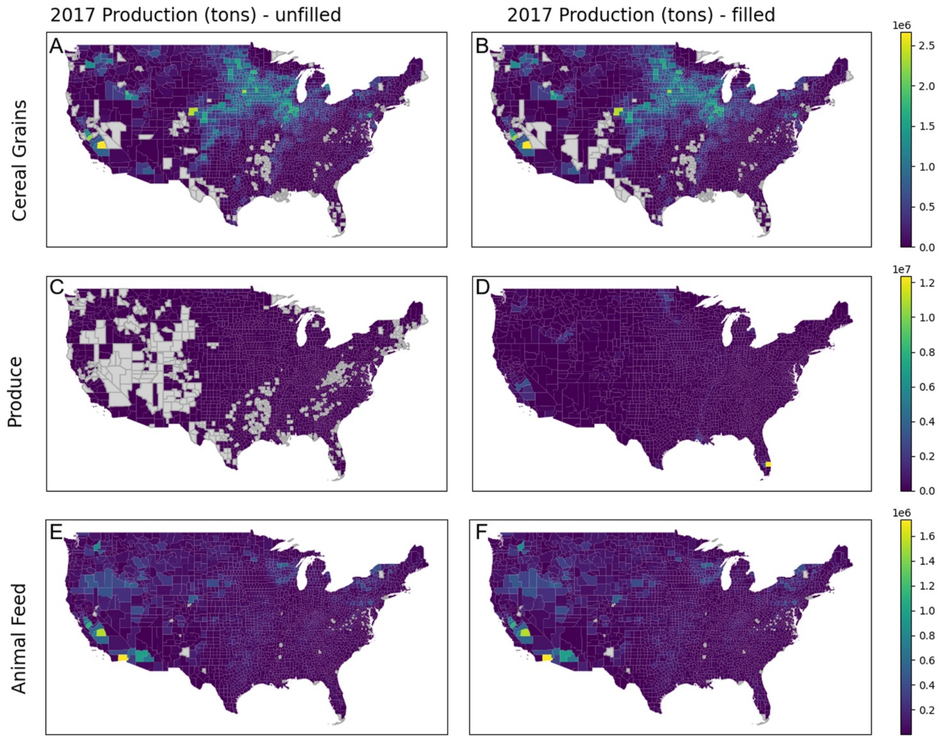

Figure 1. Unfilled and Filled (processed) production data [*tons*] for all crop categories in 2017. Rows are crop categories while columns designate unfilled or filled values. Gray counties reported zero production in 2017. (a) Cereal Grains (Unfilled); (b) Cereal Grains (Filled); (c) Produce (Unfilled); (d) Produce (Filled); (e) Animal Feed (Unfilled); and (f) Animal Feed (Filled).

these two data to generate crop-specific VWC estimates for 2012 and 2017. Crop-specific VWC data and spatial plots for each of the crop-specific estimates can be found in Supporting Information S1.

VWC [m^3/ton] is a necessary, intermediate variable in order to quantify VWT [km^3], as explained in Section 2.4.

2.4. Calculating Virtual Water Transfers

Using VWC (m^3/ton), we can calculate the virtual water contained in individual trade flows, here termed VWT [m^3]:

$$VWT_{o,d,c,w,y} = VWC_{o,c,w,y} \times F_{o,d,c,w,y} \tag{2}$$

where F is agricultural commodity flow (ton), o is origin county, d is the destination county, c is crop category, w is water source, and y is year.

3. Results

Here we address our research questions and provide estimates of VWC and VWT by crop category, water source, and drought versus non-drought year within the CONUS. We begin by comparing several key variables in our study in drought and non-drought conditions as shown in Figure 2. Production and exports decline during drought, as expected (see top two sub-plots of Figure 2). However, irrigation withdrawals are higher during drought, indicating that more blue water is required to maintain even lesser production and exports (see bottom sub-plot of Figure 2).

3.1. How Is VWC Spatially Distributed?

Maps of VWC for non-drought conditions (2017) are shown in Figure 3 for all crop category and water source combinations. Importantly, these maps are constructed from values after winsorizing; this is done to reduce large

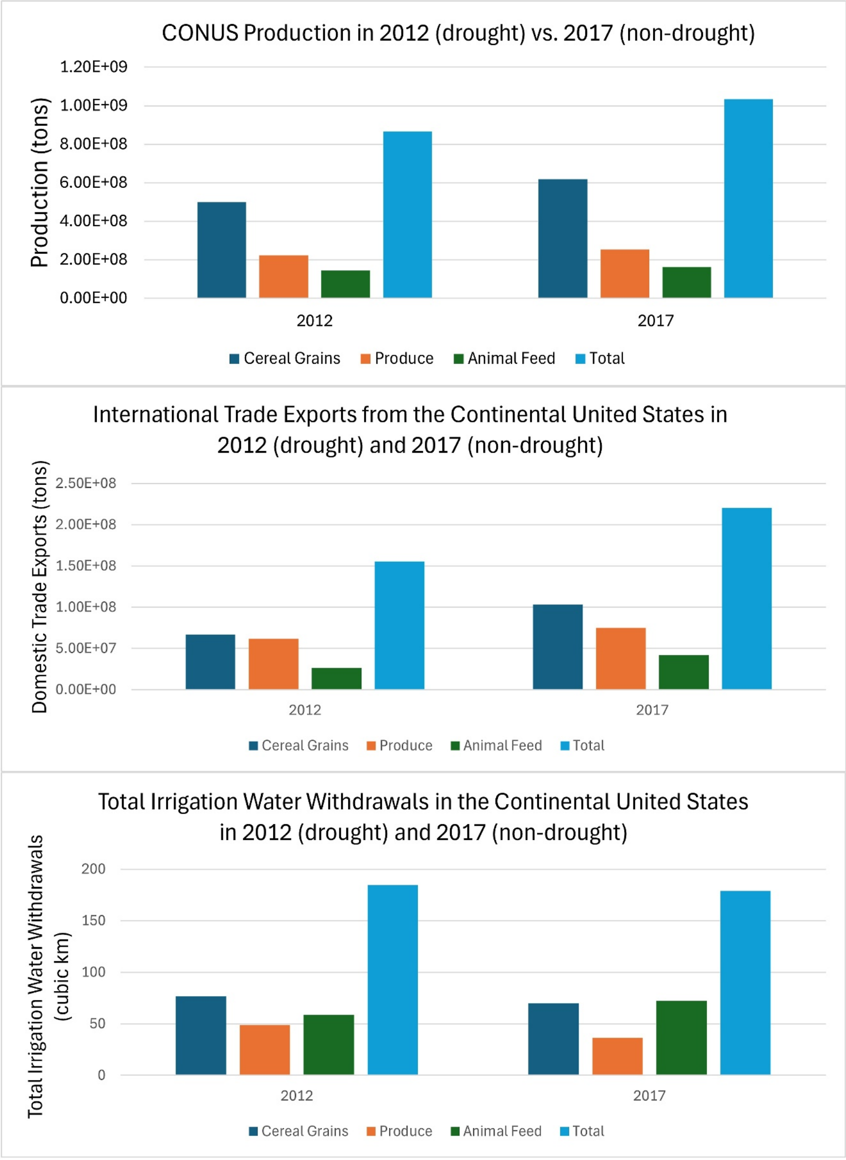

Figure 2. A comparison of agricultural production, U.S. international exports, and Irrigation Water Use (IWU) in a drought year (2012) and a non-drought year (2017) in the Continental United States for Cereal Grains (Standard Classification of Transported Goods (SCTG) 2), Produce (SCTG 3), and Animal Feed crops (SCTG 4). Production (top) comes from the USDA agricultural census data. International Exports (middle) are the sum of mass fluxes originating in the U.S. and flowing to other countries. IWU (bottom) are the sum of surface water withdrawals and groundwater withdrawals. "Total" is the sum of SCTG groups 2, 3, and 4.

outliers and make the spatial variability of the maps easier to interpret visually. Because this data has been winsorized, all maximum-value counties in each map will have the exact same value. Additionally, maps for the same crop category are all plotted to the same maximum values to enable more meaningful visual comparisons across water source categories.

In Figure 3 we show that there is significant variability not only across crop categories, but especially across water sources. The largest values are very clearly SWW, meaning that most crops are irrigated with a larger volume of SW than groundwater. This is true across crop categories, though the largest differences are visible in the animal feed category, especially in Colorado, New Mexico, and Wyoming, where SWW VWC contains the largest values while GWA VWC is low by comparison. The opposite is true in some places, with groundwater

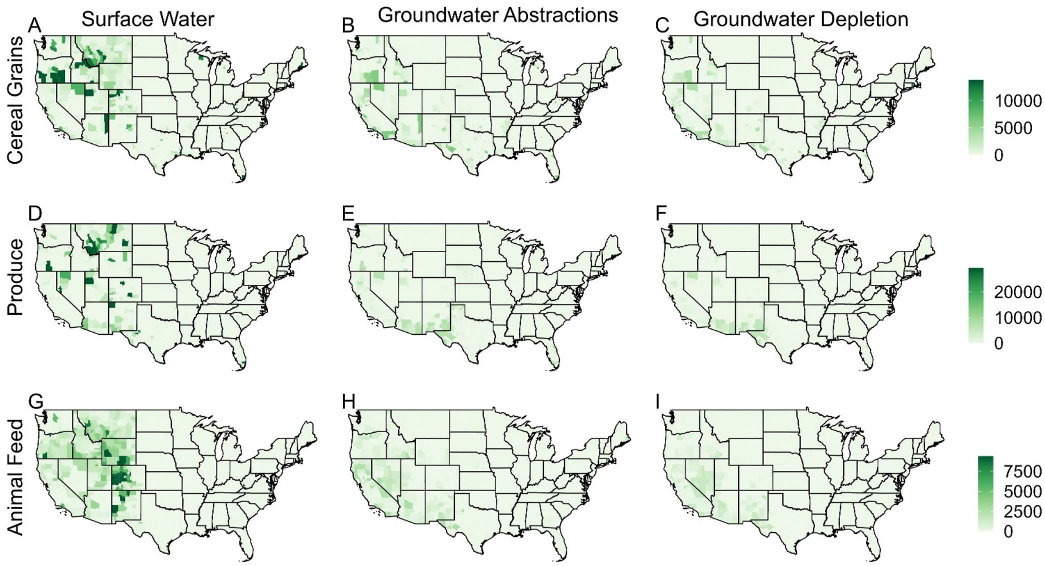

Figure 3. Virtual Water Content $\left[m^3/ton\right]$ for all crop categories and water sources in non-drought conditions (2017). Rows are crop categories while columns are water sources. (a) Cereal Grains (Surface Water Withdrawals (SWW)); (b) Cereal Grains (GWA); (c) Cereal Grains (GWD); (d) Produce (SWW); (e) Produce (GWA); (f) Produce (GWD); (g) Animal Feed (SWW); (h) Animal Feed (GWA); (i) Animal Feed (GWD).

contributing more volume per unit mass produced, such as in parts of California, southeastern New Mexico, and west Texas. Looking across crop groups we see that produce has the largest total VWC values, followed by cereal grains and lastly animal feed.

Focusing on SWW specifically, we show that SW irrigation for cereal grains is most prevalent in southern Oregon, along the northern half of the New Mexico/Arizona border, and in parts of Utah and Idaho. Knowing that most cereal grains in the US are grown in the Midwest, this is not immediately intuitive. We interpret this trend as being representative of the larger irrigation water demands for western crops, such that cereal grains grown in arid western states have higher (irrigation) VWC due to their comparatively lower crop water productivity. SWW VWC for produce is similarly scattered across the Western states though with less visible clustering, with large values in counties across the Northwest in particular. This sparser spread is likely due to produce crops being more specialized and often grown regionally. Animal feed SWW VWC is instead less concentrated than the other two crop categories, with more widely spread representation across all Western states, with the largest values focused in Colorado, Wyoming, and New Mexico. Animal feed likely has numerous neighboring counties with significant SWW values for two reasons: 1. Animal feed is largely SW irrigated, with groundwater abstractions making up a smaller fraction of these VWC values when compared to the other two crop categories; and 2. Alfalfa/hay is grown over huge portions of the western US in large fields, so animal feed (unlike produce) is very spread out relative to its weight.

GWA VWC follows similar spatial trends as SWW VWC, with a few notable differences. Across all crop types, California largely dominates GWA VWC values everywhere, probably stemming from two reasons: 1. California is extremely fertile and therefore grows many different crops (therefore showing up in all crop categories), and 2. California is extremely arid and famously relies heavily on local groundwater stores to meet its irrigation demands. While produce values may intuitively be most concentrated in California, we see large values also present in southern Arizona and New Mexico, as well as western Texas; this likely results from fairly large cotton production in some of these counties. Alfalfa is similarly grown in these regions, making some of these counties show up in the Animal Feed category as well.

GWD VWC mimics GWA VWC trends while highlighting where groundwater is being used unsustainably. For example, Klamath county in southern Oregon shows significant GWA VWC for produce commodities, but is not visible at all on the GWD VWC produce map. This implies that the groundwater embedded in produce crops grown in Klamath, OR is largely sustainable. We also gain insight looking at the SWW VWC for produce in

Klamath, OR, showing us that SW contributes more to the overall VWC of produce in this county, with (sustainable) groundwater effectively contributing the remainder of VWC. Finally, a reminder: while we may expect larger numbers for groundwater abstractions in produce, we must remember that these are VWC values and therefore represent the crop water productivity, not absolute water use.

3.2. How Does VWC Compare Between a Drought and Non-Drought Year?

Figure 4 shows how VWC varies during drought and non-drought, broken down by both SCTG and water source. VWC is mostly higher in the drought year, which makes sense, since more irrigation water is required for less mass production, as shown in Figure 2. Table 3 provides values of VWC in a drought versus non-drought year by SCTG and water source. VWC is higher in drought conditions for surface and total water sources. However, groundwater VWC (mostly) goes down during drought at the national scale. This could be due to gains in crop yields when groundwater pumping is applied during drought.

Figure 5 provides maps that show the difference between VWC in drought and non-drought conditions. Like the maps in Figure 3, these maps are constructed from the winsorized VWC values, as described in the methods. Unlike the VWC maps in Figure 3, these VWC difference maps (Figure 5) are not plotted to the same maximum values across crop categories; we do this for clarity, as normalizing across crop categories makes all groundwater differences very difficult to see.

Looking at the maps, we show that the largest differences occur in the SWW values. This is intuitive considering that the largest VWC estimates are in embedded SWW. Considering extreme values, we see that cereal grains having the largest differences, followed by produce and lastly animal feed. This is uniformly true across different water sources, though with varying magnitudes.

As 2012 was a drought year across much of the US, we expected more IWU in 2012 than in 2017 to compensate for the lack of precipitation. However, because these maps represent changes in VWC, we can only observe changes in crop water productivity, which showed both increases and decreases across the country between the 2 years studied. This variability makes sense from a drought perspective, as different parts of the CONUS experience different magnitudes of precipitation scarcity, have varied access to surface and groundwater resources to compensate, and grow different crops with different water dependencies.

Across SWW VWC differences, cereal grain VWC has visibly increased along the Arizona/New Mexico border and parts of California (GWD), with some decreases in Wyoming and southern New Mexico especially. This shows that the Arizona/New Mexico border, for example, used more SW per cereal grain crop produced in 2017 than in 2012 (represented by the increase in VWC between these years), meaning water was used less efficiently in 2017 compared to the 2012 drought. Note that there tend to be increases around this border in groundwater for cereal grains as well. This makes sense from a water savings perspective, in which case we would expect to see increases in VWC across the regions most affected by the 2012 drought. In contrast, we also show decreases when comparing the 2 years, such as along this same Arizona/New Mexico border when instead considering produce crops.

Produce VWC was smaller in a non-drought year (2017) along the Arizona/New Mexico border, meaning that less water (across all water types) was used to grow produce crops in this region during a non-drought year (2017) than during a drought year (2012). This may be due to overwatering in efforts to mitigate the impact of the drought on produce crops in this region. Most regions seem to mimic the change seen along the Arizona/New Mexico border, with cereal grain VWC being larger and produce VWC being smaller in a non-drought year (2017), as compared to a drought year (2012).

Animal feed VWC changes differently than the other two crop categories, most notably when considering groundwater VWC (both GWA and GWD) in both northern and southern California, as well as in southern Nevada. In these areas we show groundwater being used less efficiently in 2017 (higher VWC). This may result from the 2012 drought, wherein producers chose to prioritize irrigating high value produce crops with groundwater over animal feed crops, resulting in changes to groundwater irrigation patterns.

While the 2012 drought caused heavy yield reductions for California produce, we note that there are no significant changes in total GWA nor GWD VWC values in California in the non-drought year of 2017 relative to the 2012 drought (see Supporting Information S1). This means that, while groundwater use changed due to the drought, the

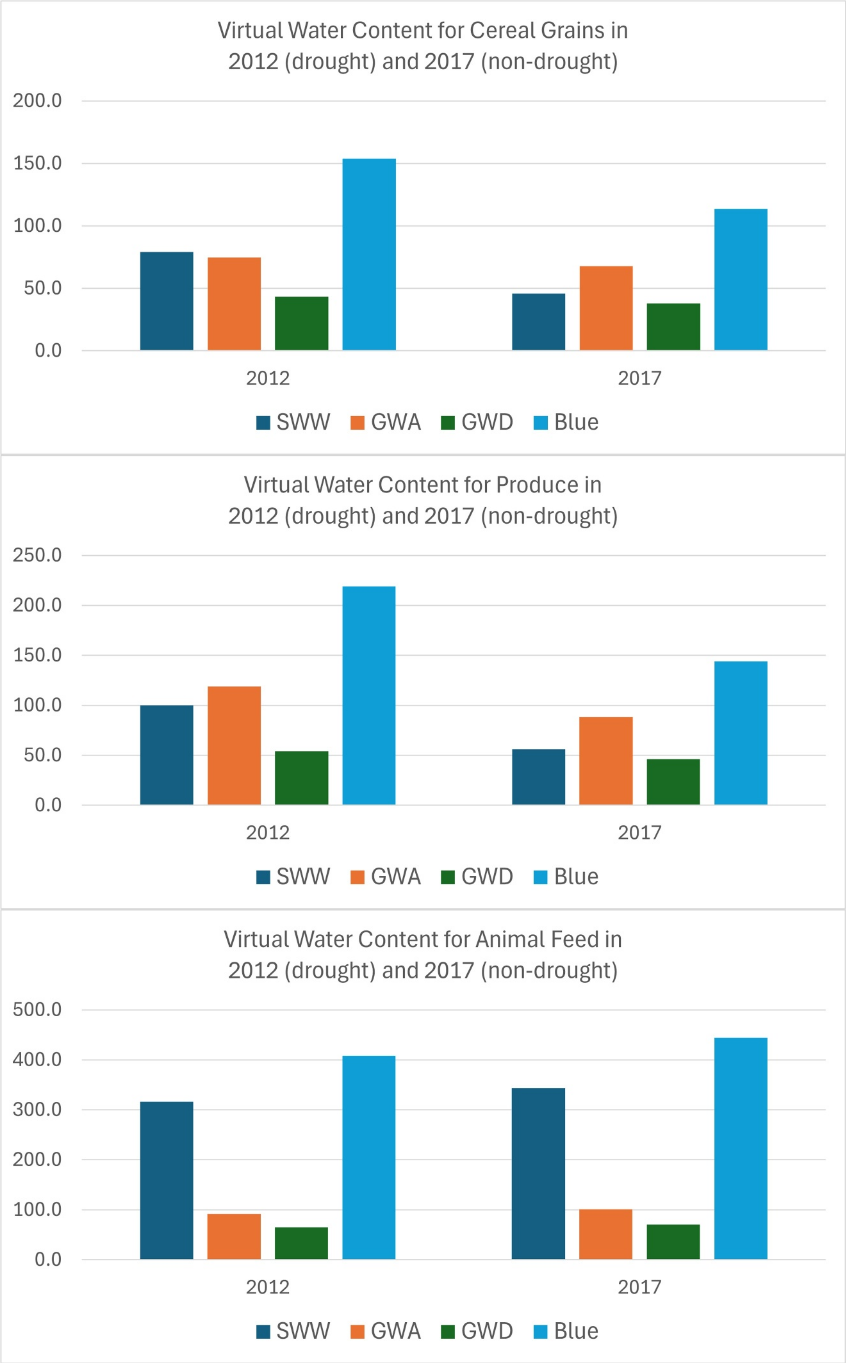

Figure 4. Virtual Water Content (VWC) $\left[m^3/ton\right]$ in a drought versus non-drought year by both water source and crop commodity group. The largest source of irrigation is surface water, followed by groundwater withdrawals. Note that groundwater depletion is a fraction of groundwater withdrawals, so total blue VWC is the sum of surface VWC and groundwater VWC.

total amount of embedded water in California produce commodities stayed fairly consistent when comparing these 2 years. This corroborates research in California's Central Valley showing that farmers fallowed land to reduce volumetric irrigation requirements and switched to more valuable crops, such as produce crops, to maximize their value during the drought (Marston & Konar, 2017).

Table 3
Values of Virtual Water Content $[m^3/ton]$ *in a Drought Versus Non-Drought Year by Water Source*

	Cereal grains	Produce	Animal feed
Blue, drought	154	219	408
Blue, non-drought	114	144	445
Surface, drought	79	100	316
Surface, non-drought	46	56	343
Groundwater, drought	75	119	92
Groundwater, non-drought	68	88	101
Depletion, drought	43	54	65
Depletion, non-drought	38	46	70

Note. "Total" refers to total irrigation (blue water) withdrawals, "surface" refers to surface water withdrawals, "groundwater" refers to groundwater withdrawals', and "depletion" refers to groundwater depletion. Surface VWC is higher in drought conditions, due to higher evaporative demands as well as lower productivity during drought. Groundwater VWC goes down in drought at the national scale, likely due to spatial heterogeneity in drought impacts and conjunctive water use.

3.3. How Is VWT Spatially Distributed?

Maps of VWT in non-drought conditions (2017) are shown in Figure 6. These maps only include transfers between different counties, as within-county transfers cannot be visualized in this way. As with all VWT values throughout this paper, we include only domestic transfers and do not include international trade links. For ease of interpretation and visual clarity, we further include only the top 5% of VWT links (ranked volumetrically) in each map. Finally, because VWT is estimated using the winsorized VWC values, the influence of the winsorization can also be seen on these results.

SWW VWT for cereal grains is most heavily concentrated from Washington state to Colorado. Produce SWW VWT is most significant in Florida, with GWD seeing the largest transfers in California. Regarding Animal Feed, the most significant links are located within southern California, with lesser links in Colorado, southern Idaho, and northern California. The largest SWW VWT cereal grain transfers go to Seattle, WA, for further processing and international export. SWW VWT cereal grain transfers also are significantly larger within western Colorado, including a large link between Washington and Colorado states as well as lesser links all throughout Washington and Idaho. These linkages effectively connect the Midwest Corn Belt where most cereal grains are grown, to the West coast and its international ports exporting agricultural goods.

We show similar SWW VWT patterns when instead considering animal feed, particularly around the larger cities of Boise, ID and Denver, CO. Despite these similarities, the largest transfers of SWW VWT in animal feed are in the metropolitan area around Los Angeles, CA, as well as extremely high VWT network density of smaller transfers all along the California Central Valley. This contrasts with produce SWW VWT, which is visible in California but does not dominate as much as in the animal feed category. This is the result of SWW VWT for produce being dominated by a transfer link across the Washington/Oregon border and two links near Miami, FL, which dominate other links in this category. These links are large due to their large VWC values (a result of large irrigation volumes divided by small crop production) coupled with large transfer estimates.

In the groundwater VWT categories, we show much more significant skew toward notably arid regions with aquifers, specifically the northern portion of the High Plains aquifer extent and most of the Central Valley area in

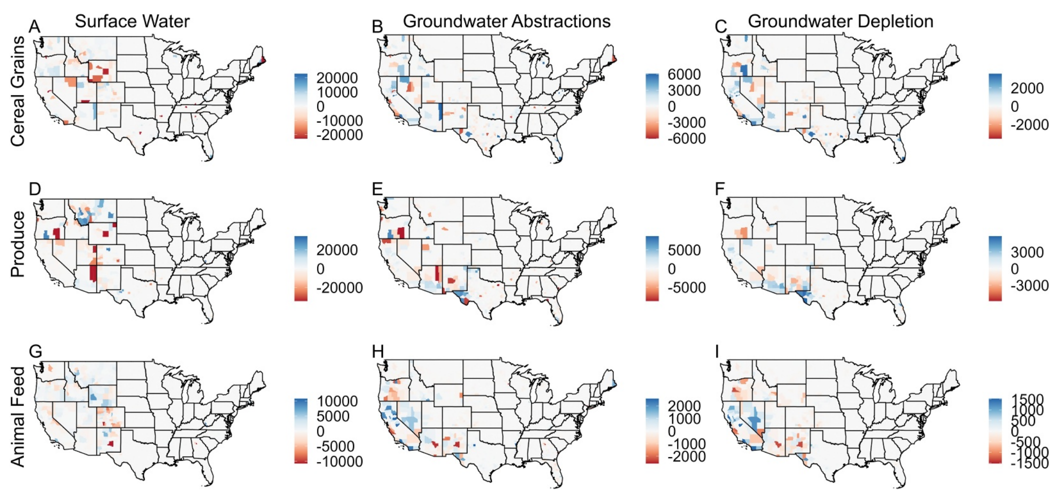

Figure 5. Virtual Water Content $[m^3/ton]$ difference between drought (2012) and non-drought conditions (2017) (calculated as 2017 minus 2012) for all crop categories and water sources. Rows are crop categories while columns are water sources. (a) Cereal Grains (Surface Water Withdrawals (SWW)); (b) Cereal Grains (GWA); (c) Cereal Grains (GWD); (d) Produce (SWW); (e) Produce (GWA); (f) Produce (GWD); (g) Animal Feed (SWW); (h) Animal Feed (GWA); (i) Animal Feed (GWD).

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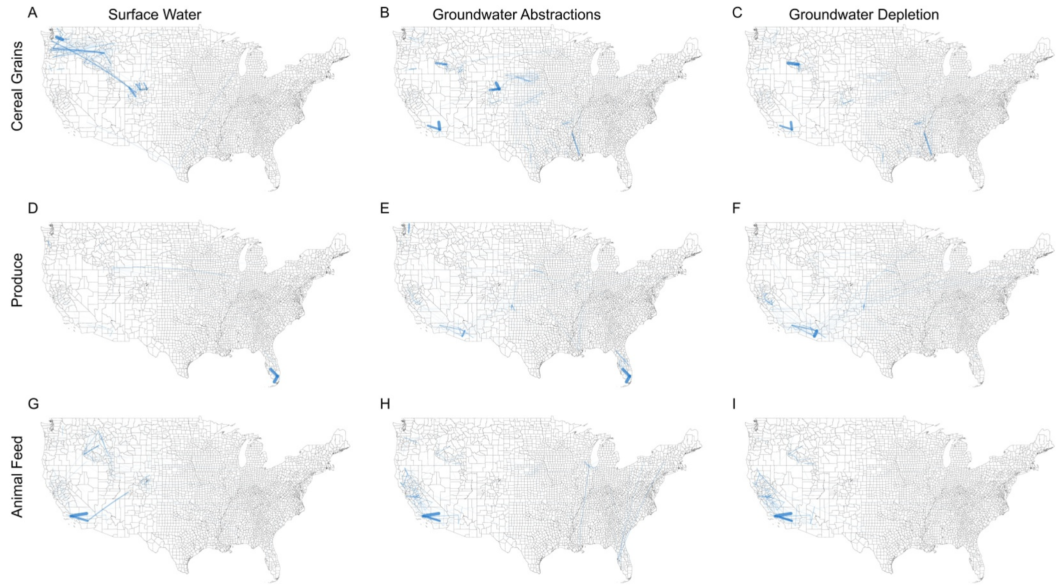

Figure 6. Virtual Water Transfers $\left[m^3\right]$ for all crop categories and water sources in 2017. Only the top 5% of links (in terms of volumetric water value [m^3]) are shown for clarity. Within-county transfers (self-loops) are excluded from this visualization. Rows are crop categories while columns are water sources. (a) Cereal Grains (Surface Water Withdrawals (SWW)); (b) Cereal Grains (GWA); (c) Cereal Grains (GWD); (d) Produce (SWW); (e) Produce (GWA); (f) Produce (GWD); (g) Animal Feed (SWW); (h) Animal Feed (GWA); (i) Animal Feed (GWD).

California. GWA VWT of cereal grains is where the High Plains aquifer shows up most visibly, which is unsurprising considering these parts of Nebraska and Kansas mostly grow cereal grains. Washington state is similar in that the groundwater used in the eastern part of the state, concentrated around the Tri-Cities region, seems to primarily be sustainable groundwater embedded in transferred cereal grains. The largest groundwater VWT values for cereal grains are actually concentrated in the southern part of Idaho around and between Boise, ID and Idaho Falls, ID, while similarly large values are transferred around metropolitan Los Angeles.

When reviewing groundwater VWT of animal feed, we instead show that the vast majority of transfers occur throughout California, particularly in GWD VWT, which has the added advantage of not being visually minimized by the large Florida link from Indian River to Lafayette county seen in other maps. GWD VWT for produce is particularly concentrated over the northern part of the Central Valley aquifer, with moderate values around San Francisco but larger values occurring inland between San Joaquin and Amador, and Fresno and Mariposa counties. Of note, many GWD VWT links of produce are visible from this part of California to the rest of the country, which is consistent with our understanding that California not only grows a majority of the country's produce, but that this produce is often reliant on groundwater depletion from the Central Valley aquifer system.

3.4. How Does VWT Compare Between a Drought and Non-Drought Year?

Figure 7 shows how VWT varies during drought and non-drought, broken down by SCTG and water source. VWT is higher in non-drought, which is different to VWC. This highlights that VWT is most influenced by commodity flux values rather than the water productivity of crops. In other words, VWT is higher in a non-drought year, when commodity production and transfers are high. Table 4 shows that the largest reduction in drought is for SW withdrawals embedded in grain supply chains. The virtual transfers of groundwater irrigated crops are less impacted during drought, since groundwater pumping acts to buffer production and hence supply chains during drought.

Table 4 shows that virtual water transfers are larger than total irrigation withdrawals. This is because there is double counting in the FAF mass flux data used to estimate county-level flows by Karakoc et al. (2022). This means that our approach can capture spatially detailed water-risks embedded in domestic supply chains, but that input-output accounting methods should be used to avoid this issue with double counting in future work,

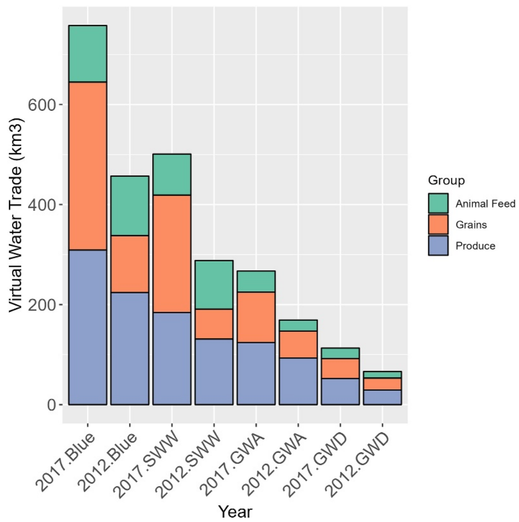

Figure 7. Virtual Water Transfers (VWT) $[km^3]$ in a drought versus non-drought year by both water source and crop commodity group. VWT is largest for each water source in non-drought. However, there is a large loss in VWT of surface irrigation for grains during drought.

particularly in order to calculate consumption-based water footprints. We do not calculate consumption-based water footprints in this study due to this issue with double counting.

We examine differences in link-level VWT from drought to non-drought in Figures 8 and 9. Links in Figure 8 are those that were smaller in the drought. These are links that are large during non-drought conditions, but that shrink when there is a drought. Links in Figure 9 are those that were greater during drought. These links may represent adaptive capacity in the system, which become more pronounced with drought. Changes in link-level VWT around drought could help to identify exposure to unsustainable groundwater use in supply chains, a potential future risk facing supply chains.

3.5. How Much VWT Is Exported Versus Transferred Domestically?

While the FFM only includes domestic transfers (Karakoc et al., 2022), we can use FAF transfer data (ORNL, 2022) coupled with aggregated VWT data to get a broad understanding of how much VWT is transferred domestically versus exported internationally. Figure 10 summarizes this fractional difference across both study years by FAF tonnage and VWT, with VWT separated into different water source categories and SCTG commodity groupings.

Reviewing the plots we see that the vast majority of VWT stays domestic, making up around 80%–90% across variables for both years. Groundwater-related VWT (GWA and GWD) seems to contribute more when considering cereal grains (SCTG 2), while SW seems to contribute more to produce (SCTG 3) VWT exports. Animal feed (SCTG 4) is consistently lower than the other two SCTG groups in terms of VWT exports.

Interestingly, there appears to be high variability when comparing 2012 to 2017, particularly within groundwater-related VWT for cereal grains (SCTG 2) which went up nearly 15% when comparing drought (2012) to non-drought conditions (2017). Another significant change can be seen in SW VWT of produce (SCTG 3), which decreased about 10% between the 2 years. The driver in these changes is unclear from this study alone, as this can be influenced by any variety of things including global food markets, yields, prices, etc. While the cause remains unclear, understanding how these values change over time is valuable for assessing the coupled water and food security of the US.

Table 4
Values of Commodity Flows (F) [Tons] and Virtual Water Transfers $[km^3]$ *in a Drought Versus Non-Drought Year by Water Source*

	Cereal grains	Produce	Animal feed
Commodity flows, drought	8.7 E + 08	4.4 E + 08	2.9 E + 08
Commodity flows, non-drought	1.3 E + 09	7.1 E + 08	4.4 E + 08
Total, drought	114	224	119
Total, non-drought	336	309	113
Surface, drought	60	131	96
Surface, non-drought	235	184	72
Groundwater, drought	54	93	22
Groundwater, non-drought	101	124	42
Depletion, drought	24	29	13
Depletion, non-drought	39	52	21

Note. "Total" refers to total irrigation (blue water) withdrawals, "surface" refers to surface water withdrawals, "groundwater" refers to groundwater withdrawals', and "depletion" refers to groundwater depletion. Note that total blue irrigation is the sum of surface and groundwater components, but not depletion, which is a sub-set of groundwater withdrawals. F goes down in drought. VWT is higher in non-drought conditions across water sources, driven by changes in F. Animal feed VWT from surface/total water sources are the exception, due to increased VWC of animal feed from surface/total sources during drought.

To further our understanding of VWT exports, we separated VWT exports by destination in Figure 11. While differences between the years are less prevalent fractionally, one interesting change to note is the GWD VWT present in cereal grains (SCTG 2), which was largely exported to Mexico in 2012 but then changed to mostly be exported to "Rest-Americas" (South and Central America) in 2017. This shift in fractional distributions is likely a result in changes to the total cereal grain GWD VWT values between these two years, varying widely from roughly 1.2 million m^3 in 2012 up to 8.9 million m^3 in 2017. A similar notable difference is seen for produce GWA VWT, which was primarily exported to East Asia in 2012 but switched to Canada being the predominant recipient of CONUS exports in 2017; total GWA VWT decreased from 9.0 million m^3 in 2012 to 6.7 million m^3 in 2017.

Besides these categorically specific trends, we can also notice general differences between drought (2012) and non-drought conditions (2017). The most obvious difference is the fractional decrease in the East Asia category (the blue-gray color), which across almost all categories were smaller in non-drought conditions (2017) than in drought (2012). The Canada and the "Rest-Americas" categories instead seem to generally increase when comparing these 2 years, with other export destinations maintaining similar

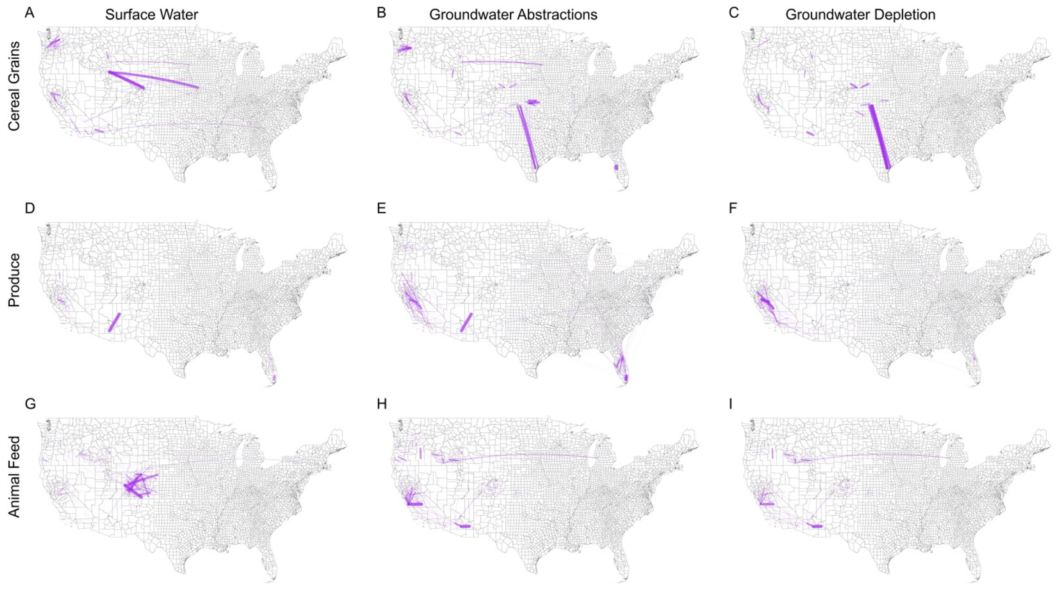

Figure 8. Negative differences in Virtual Water Transfers (m^3) for all crop categories and water sources from drought to non-drought. The differences in flows were calculated as 2012 minus 2017 flows: Negative trade links are links where the flow in 2012 was less than in 2017. Only the top 5% of negative trade links are shown for clarity. Within-county transfers (self-loops) are also excluded from this visualization. Rows are crop categories while columns are water sources. (a) Cereal Grains (Surface Water Withdrawals (SWW)); (b) Cereal Grains (GWA); (c) Cereal Grains (GWD); (d) Produce (SWW); (e) Produce (GWA); (f) Produce (GWD); (g) Animal Feed (SWW); (h) Animal Feed (GWA); (i) Animal Feed (GWD).

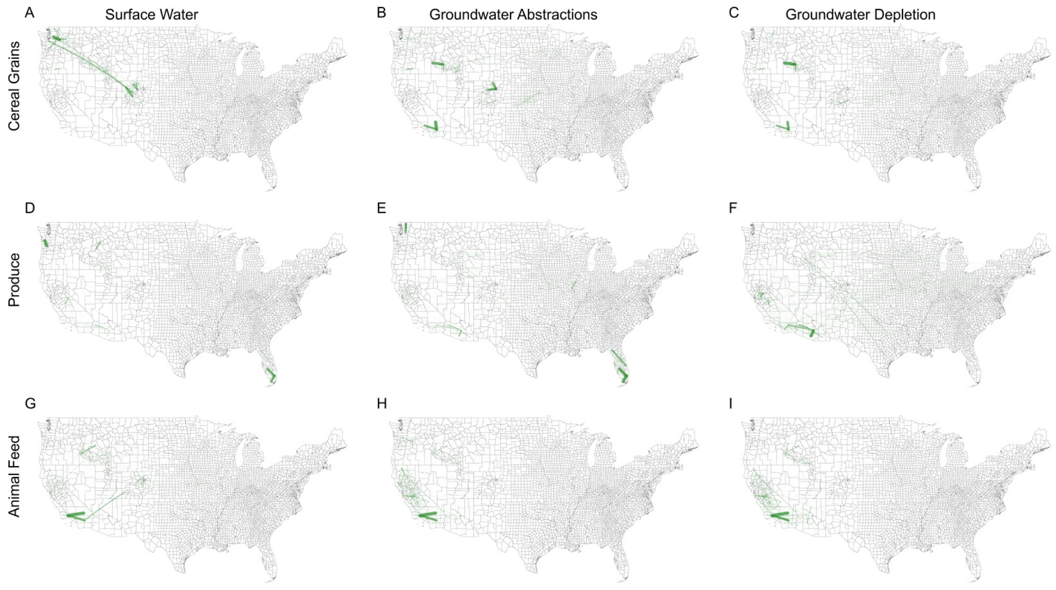

Figure 9. Positive differences in Virtual Water Transfers (m^3) for all crop categories and water sources from drought to non-drought. The differences in flows were calculated as 2012 minus 2017 flows: Positive trade links are links where the flow in 2012 was greater than in 2017. Only the top 5% of positive trade links are shown for clarity. Within-county transfers (self-loops) are also excluded from this visualization. Rows are crop categories while columns are water sources. (a) Cereal Grains (Surface Water Withdrawals (SWW)); (b) Cereal Grains (GWA); (c) Cereal Grains (GWD); (d) Produce (SWW); (e) Produce (GWA); (f) Produce (GWD); (g) Animal Feed (SWW); (h) Animal Feed (GWA); (i) Animal Feed (GWD).

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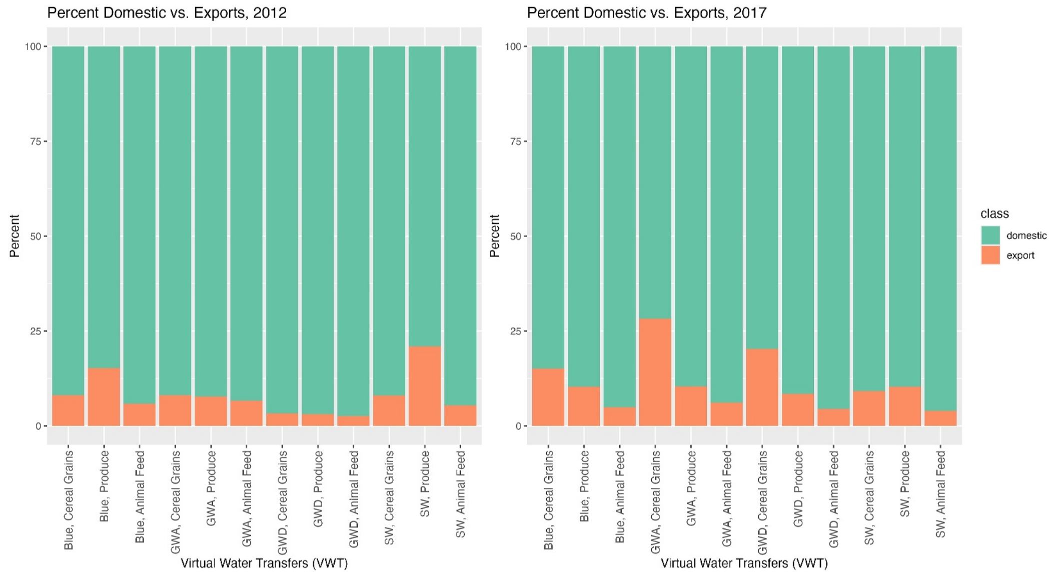

Figure 10. Percent Virtual Water Transfers (VWT) [%] Exports versus Domestic Transfers (including self-loops). Left figure shows drought values (2012), while right figure shows non-drought (2017). *X*-axis variables designate VWT variables specifying water source: groundwater abstractions (GWA), groundwater depletion (GWD), surface water (SW), and blue (sum of GWA + SW). Number following variable label designates the Standard Classification of Transported Goods group (2: Cereal grains, 3: Produce, 4: Animal Feed). Values are calculated by aggregating VWT to Freight Analysis Framework zones to determine exports versus domestic transfers, then summing over the entire CONUS for each variable category.

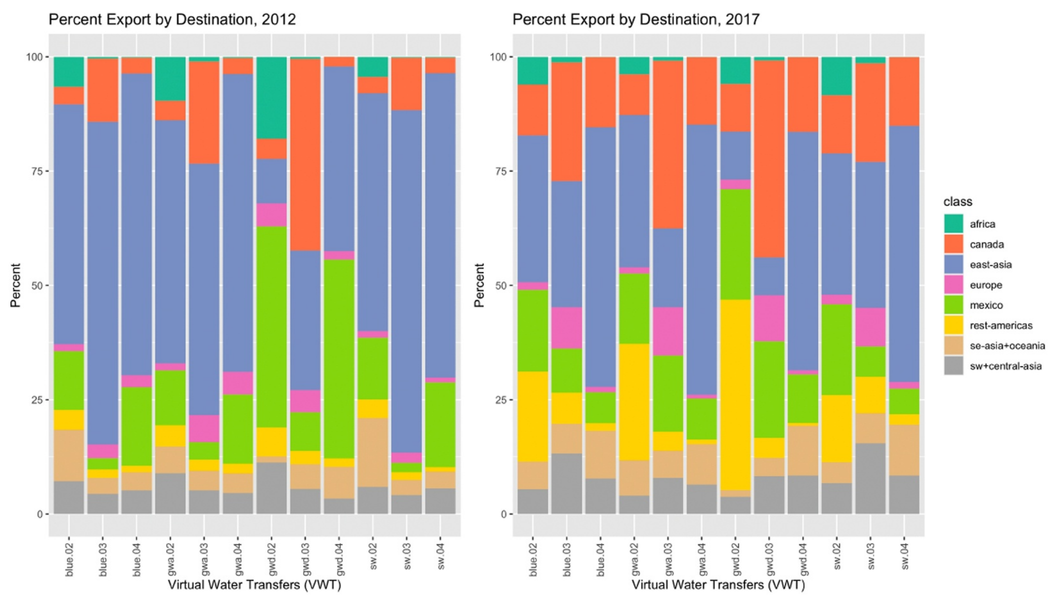

Figure 11. Percent Virtual Water Transfers (VWT) [%] Exports only, by destination. Left figure shows drought values (2012), while right figure shows non-drought (2017). *X*-axis variables designate VWT variables specifying water source: groundwater abstractions (GWA), groundwater depletion (GWD), surface water (SW), and blue (sum of GWA + SW). Number following variable label designates the Standard Classification of Transported Goods group (2: Cereal grains, 3: Produce, 4: Animal Feed). Values are calculated by aggregating VWT to Freight Analysis Framework zones to determine exports versus domestic transfers, then summing over the entire CONUS for each variable category.

Table 5
Blue Virtual Water Content [m^3/Ton] for Crop Categories From Mialyk et al. (2024) for Comparison With Our Values

VWC $[m^3/ton]$	Cereal grains	Produce	Animal feed
2012, Mialyk et al. (2024)	223	221	43
2012, this study	155	215	408
2017, Mialyk et al. (2024)	140	207	27
2017, this study	115	148	445

Note. Note that the Mialyk et al. (2024) values presented in this table are the simple mean across the individual crops contained within these crop groups.

fractional receipts of CONUS VWT exports. For tables describing particular total export values to particular export categories, see the Supporting Information S1.

4. Discussion

4.1. Comparison With Other Published Results

Here we compare our estimates against some values from the literature. Many previous studies estimate the *consumptive* water footprints of crop production. Our values will differ because we examine the *withdrawal* water footprints of crop production, since our VWC values are based on irrigation withdrawal estimates from Ruess et al. (2022). Consequently, we expect our values to be larger than corresponding consumptive values.

To assess our VWC values across crop categories, we compare our results to Mialyk et al. (2024) in Table 5. Our estimates of blue VWC in m3/ton compare well with Mialyk et al. (2024) for cereal grains and produce crop categories. This is notable because we estimate withdrawal-based VWC while Mialyk et al. (2024) examine consumptive-based water footprints. However, while cereal grains and produce results match fairly well, our animal feed VWC estimates are significantly larger than those calculated by Mialyk et al. (2024). This likely results from two key differences when comparing methods of estimating alfalfa VWC, which is a key crop within the animal feed crop category in Ruess et al. (2022).

The first key difference is that while we use empirical information on crop *production* in this study for the denominator of VWC, Mialyk et al. (2024) instead modeled crop *yield* with global input data in the AquaCrop model. It is possible that modeled yield estimates of alfalfa in AquaCrop are larger than realized production from USDA statistics, which helps to explain why our VWC values for animal feed are larger than those provided by Mialyk et al. (2024).

Second, these differences in animal feed VWC likely result from the fact that Ruess et al. (2022) apply multi-cropping throughout the entire alfalfa growing season (see Supporting Information S1), while Mialyk et al. (2024) do not include multi-cropping for alfalfa. Alfalfa growing seasons can be tricky to properly model, seeing as in the U.S. alfalfa is typically harvested 3–4 times per year in northern zones, but can be harvested up to 10–11 times in more arid regions of the country throughout the Southwest (Fernandez et al., 2019). This difference in modeling alfalfa is likely a key factor in why our VWC for animal is larger than those in Mialyk et al. (2024). Importantly, our VWC for animal feed is in line with other published studies for the U.S., such as the average US alfalfa VWC estimate of 678 m^3/tonne in Mubako and Lant (2013).

Importantly, we include data on alfalfa locations in the different years of our study from Cropscape, which means that we capture how harvested areas change during drought and non-drought years. However, we don't have any information on the number of plantings within a growing season for the years of our study. Capturing the number of plantings is a unique challenge for alfalfa due to its many plantings and flexibility to reallocate water when it is scarce. This means that future research is needed to understand the number of alfalfa plantings, and how that behavioral response represents a potential adaptation measure of farmers during drought that we are not able to capture with our current methods.

4.2. Data Dependencies and Underlying Assumptions

This study relies very heavily on recently published data sources, all relying on their own sets of assumptions. These data sets are USDA NASS QuickStats (USDA, 2022), the IWU data set (Ruess et al., 2024), and the FFM data set (Karakoc et al., 2022).

USDA NASS QuickStats (USDA, 2022) hosts the best available production data collected in the United States for the entire CONUS area. However, some crops included in our crop categories did not have production data available as census data, while others were unavailable entirely. In cases where crop data was available, we had to estimate redacted counties, potentially introducing error into our results. Where crop data was unavailable as census data, we often turned to survey data, which is less resolved than census data. Where neither census nor survey production data were published, we estimate production using harvested area and yield data. When yield

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data was unavailable at the county level, we estimate it from agricultural district, state, or even national-scale published yield data. If production could not be calculated, we was forced to entirely omit the crop in question. Finally, the production of many crops was published in different mass units, necessitating unit conversions which may result in rounding errors.

The IWU data set (Ruess et al., 2024) is modeled using a global modeling framework (Ruess et al., 2022; Sutanudjaja et al., 2018). This of course means that certain intricacies of the CONUS hydrological system may not have been captured ideally. However, the IWU data set results were scaled to United States Geological Survey values (Ruess et al., 2024), meaning that total water allocations are consistent with widely accepted published data. See (Sutanudjaja et al., 2018) for further details about the model and its underlying assumptions. See (Ruess et al., 2022, 2025) for further details about the results and the assumptions necessitating for modeling the irrigation allocations across crop categories and water sources.

Briefly, the IWU data set is subject to significant limitations owing to both its construction and validation (Ruess et al., 2022, 2024). PCR-GLOBWB 2 relies on many input data sets which themselves have limitations (2008–2020 year restriction due to input constraints; irrigation efficiency data linearly extrapolated to unreported years; crop coefficients aggregated to represent crop groups rather than individual crops), while the model itself is also limited in that irrigation water demands always use SW resources before allocating groundwater to meet irrigation demands (Ruess et al., 2022; Sutanudjaja et al., 2018). All input data set. also have their own uncertainties which are largely undocumented and consequently could not be propagated through to reported IWU outputs (Ruess et al., 2022).

The FFM data set (Karakoc et al., 2022) is a statistical model expanding on previous work (X. Lin et al., 2019). This data set statistically reallocates FAF food flows (ORNL, 2022) down to the county scale. This methodology of course has biases and built-in assumptions that also influence the results of this paper. See (X. Lin et al., 2019) for further details about the original statistical methodology. See (Karakoc et al., 2022) for further details about the expansion of the statistical methods to additional years.

Lastly, we relied on winsorization to smooth outliers from our VWC calculations, which of course has an impact on our results. While this solves the problem of major outliers driving erroneous trends, it adds an element of further uncertainty to our results. This is further elaborated on in the following section.

4.3. Handling Outliers in VWC and VWT Estimates

We chose to use all input data in its native form, with the exception of the USDA NASS QuickStats production data (USDA, 2022). Due to redacted county-level information, we had to calculate production data from harvested area and yield data, and/or gap-filling redacted data based upon state or national production values. By using all data inputs in their native forms, some of our VWC and VWT results contained outliers. To address this issue, we winsorized the county VWC estimates to the 99.5% upper bound (no lower bound was used as the lowest values were already at zero). We chose the 99.5% cutoff as a reasonable balance for removing only the most extreme outliers; this kept overall county values generally comparable with state VWC values, while simultaneously not trimming too much information. The decision to winsorize the VWC data strikes a reasonable balance between maintaining the integrity of the input data and reporting realistic results.

However, even with winsorization, there remain some large VWC values. This is largely a result of comparatively small production values. For example, Hancock County in Maine has only 14 tons of cereal grains, while many other top-ranking counties produce hundreds or even thousands of tons of cereal grains. Gila, AZ and Miami-Dade, FL have similarly small production values, producing only 0.6 and 8 tons of cereal grains, respectively. These small production values paired with relatively large water use result in these counties having some of the highest VWC values in the country. The interpretation of these counties with large VWC values is that they have very low crop water productivity (e.g., large volumes of irrigation required per unit of crop produced).

4.4. Potential Applications for VWC and VWT

Recent research conceptualizing irrigation benchmarking (Marston et al., 2020) describes potential water savings by bringing river basins throughout the CONUS up to industry- and region-specific standards. These benchmarks rely on crop yield and crop water requirements, as well as cropland maps and climate information. Similar benchmarks could be calculated across the VWT network to better understand not only how each county can improve water productivity, but also how trade partnerships play into improving water productivity across the whole country. Paired with work optimizing crop reallocation (Davis et al., 2017), we could gain insights as to how the agri-food system within the US could be better optimized for water savings.

VWC estimates help us understand local crop water productivity, showing local irrigators how much water they use per unit crop mass produced. VWT communicates information both to importers and exporters of agricultural commodities: importers gain an improved understanding of their dependency on other counties across the CONUS from not only an agricultural commodity perspective but additionally a water reliance and sustainability perspective, while exporters gain insights into how much of their local water resources are being consumed outside of their county limits. This information can aid supply chain actors in assessing water sustainability and risks throughout agri-food supply chains.

Reliance on unsustainable water resources represents an emerging risk to agricultural supply chains and trade. This is because production will eventually have to be brought within sustainable limits for groundwater pumping, either when the water is no longer physically available in the aquifer, or when it is economically infeasible to access by pumping. The high-resolution estimates of VWT that we have provided by water source, county, and commodity group can help decision-makers in supply chains evaluate their water risks.

5. Conclusions

We estimate VWC $\left[m^3/ton\right]$ and VWT $\left[m^3\right]$ for three crop categories (cereal grains, produce, and animal feed) and three water sources (SW, groundwater abstractions, and groundwater depletion) for drought conditions (2012) and non-drought conditions (2017) for counties within the Conterminous United States (CONUS). VWC is higher in drought conditions across water sources, which makes sense since irrigation withdrawals are higher, while production is lower in drought. Conversely, VWT is higher in non-drought conditions, when there is plentiful production and commodity transfers. Animal Feed is an exception, which illustrates the unique attributes of this agricultural use category.

Overall, these results present a high-resolution assessment of VWC and VWT by water source and crop category, uniquely reliant on CONUS data inputs rather than global inputs. Our results could be used in future research and decision-making related to irrigation withdrawals used in production and supply chains. Future research should additionally consider the sustainability of SW irrigation, as well as other factors in the agri-food system, such as nutritional aspects of crops and related agricultural policies and practices. The way that future droughts will impact crop production and trade in the CONUS is also an important avenue of future inquiry, following this line of research for Canada (Khalili et al., 2024).

Our findings highlight that groundwater irrigation buffers crop production and supply chains during drought. This underscores the importance of sustainably managing groundwater resources so that they are available to mitigate the impact of future droughts on agricultural production and supply chains. Reliance on unsustainable groundwater resources is an emerging risk facing agricultural supply chains. We provide high-resolution estimates of VWC and VWT by water source, county, and commodity group that decision-makers can use to evaluate water risks in supply chains.

Data Availability Statement

All estimates from this study are available at the Illinois Databank (Ruess et al., 2025). These data contain estimates for Virtual Water Content (VWC) and Virtual Water Transfers (VWT) for nine unique combinations of three crop categories (cereal grains, produce, and animal feed) and three water sources (surface water withdrawals, groundwater withdrawals, and groundwater depletion) for the years 2012 and 2017 within the Continental United States. The VWC is calculated by dividing irrigation withdrawal estimates (m^3) by the production (tons) at the county resolution. The VWT is calculated by multiplying the VWC by the estimated county level food flows (tons) from Karakoc et al. (2022). All VWC estimates are provided at the county resolution according to county GEOID and are given in units of m^3/ton. All VWT estimates are given in pairs of origin and destination GEOIDs and provided in units of m^3.

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