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RESEARCH ARTICLE

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Key Points:

- Monthly crop water consumption was calculated from 1981 to 2019 for major irrigated crops in the US
- Around 10% of the irrigated croplands account for over 90% of irrigation volume
- Corn and soybeans were the most irrigated crops in eastern states, while alfalfa and hay dominated in western states

Supporting Information:

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

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Monthly Crop Water Consumption of Irrigated Crops in the United States From 1981 to 2019

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Abstract Irrigated agriculture depends on surface water and groundwater, but we do not have a clear picture of how much water is consumed from these sources by different crops across the US over time. Current estimates of crop water consumption are insufficient in providing the spatial granularity and temporal depth required for comprehensive long-term analysis. To fill this data gap, we utilized crop growth models to quantify the monthly crop water consumption - distinguishing between rainwater, surface water, and groundwater - of the 30 most widely irrigated crops in the US from 1981 to 2019 at 2.5 arc min. These 30 crops represent approximately 95% of US irrigated cropland. We found that the average annual total crop water consumption for these 30 irrigated crops in the US was 154.2 km^3, 70% of which was from irrigation. Corn and alfalfa accounted for approximately 16.7 and 24.8 km^3 of average annual blue crop water consumption, respectively, which is nearly two-fifths of the blue crop water consumed in the US. Surface water consumption decreased by 41.2%, while groundwater consumption increased by 6.8%, resulting in a 17.3% decline in blue water consumption between 1981 and 2019. We find good agreement between our results and existing modeled evapotranspiration (ET) products, remotely sensed ET estimates (OpenET), and water use data from the US Geological Survey and US Department of Agriculture. Our data set and model can help assess the impact of irrigation practices and water scarcity on crop production and sustainability.

1. Introduction

Irrigation increases crop yields and enables crop production in places where growing crops would be infeasible or less profitable with rainfall alone. In the United States, irrigated croplands contribute half of total US crop sales, despite being only a quarter of the total agricultural land being irrigated (USDA, 2019b). Irrigated crop production is responsible for approximately three-fourths of human-related water consumption in the United States (Marston et al., 2018). Though irrigation is essential in supporting food, fuel, and fiber production, we lack a temporally and spatially detailed understanding of where and when water is used for irrigation, its source, and how much is applied to each crop. Accurately assessing the magnitude, location, and timing of crop water demand is critical for understanding the sustainability of agriculture (Chiarelli et al., 2020), which has implications for water and crop management and policy.

Crops extract water within their root zone, and this water can come from rainfall (i.e., green water) or from groundwater or surface water sources (i.e., blue water). Estimates of crop water consumption (CWC; i.e., direct water footprint) should distinguish between green and blue water since these water sources have different uses and implications for both ecosystems and society (Hoekstra, 2019). Different approaches have been used to estimate crop blue and green water demand since actual measurements (e.g., water meters, lysimeters, flux towers) are rare.

Crop water demands are often estimated using farmer surveys, models, and remote sensing. In the United States, state and federal agencies have surveyed farmers to estimate irrigation applications (Dieter et al., 2018; USDA, 2019b). However, agricultural surveys and census are costly and time-consuming. Moreover, relying solely on input from farmers introduces the potential for errors and inconsistencies in the data collected since on-farm metering is very uncommon and farmers employ different methods to estimate their water use. Recently, researchers have utilized satellite observations to estimate actual evapotranspiration (ET) from croplands (Anderson et al., 2007; Melton et al., 2022; Senay, 2018). One notable example is OpenET (Melton et al., 2022), a data product that combines six models to generate an ensemble ET at 30 m resolution across the western US since 2016. These remotely sensed data products offer water use estimates across wide geographic regions using a consistent approach and data. It is important to note, however, that estimates of ET from remote sensing products do not represent a direct measurement of crop ET. Instead, satellite readings are transformed by different models to produce ET estimates, with each model potentially diverging significantly from the others (Zipper et al., 2024). Furthermore, these methods do not differentiate between blue and green water, nor can they estimate CWC for hypothetical scenarios. On the other hand, utilizing crop growth models provide an alternative means to estimate CWC consistently across large geographical areas, while also allowing for the partitioning of water use into blue and green components. These models encompass a range of approaches, from simple methods that utilize a combination of reference evapotranspiration and crop coefficients, to more complex simulations that consider crop growth dynamics based on climatic variables, soil parameters, crop characteristics, and various management strategies. However, these models can pose computational challenges, particularly with more complex simulations at large geographical scales. Additionally, CWC estimates are sensitive to input parameters, and small errors in these inputs can lead to significant variations in estimates (Zhuo et al., 2014).

There are several crop modeling studies that have estimated CWC for specific countries, as well as globally. The earliest of these studies used simplistic models to estimate annual CWC at the global (Postel et al., 1996), continental (Shiklomanov & Gleick, 1993), or country (Seckler et al., 1998) scale. Modeled estimates of CWC are becoming more spatially refined and are often provided at 5 arc min grid cells. For example, Siebert and Döll (2010) quantified the average blue and green CWC for 26 crop classes between the years 1998–2002 at a spatial resolution of 5 arc min Mekonnen and Hoekstra (2011) expanded crop coverage to 126 crops and used longer average climate conditions (1996–2005) to quantify the average annual blue and green CWC at 5 arc min. These studies, however, neglected the effects of inter- and intra-annual climate variations on CWC, which can significantly influence the water demand of crops (Chiarelli et al., 2020). They have either used long-term average climate data or focused on short-term periods to estimate annual CWC. They have also not shown how CWC changes within a year by only giving annual estimates. Chiarelli et al. (2020) improved on these studies by evaluating monthly green and blue CWC for 5 crops, as well as annual green and blue CWC for 26 crops, for 2000 and 2016 globally. Long-term trends of CWC cannot be evaluated, however, with results for only 2 years. Ruess et al. (2024) extended the time span of CWC estimates for 20 crops in the US from 2008 to 2020. Their county-level CWC estimates report annual water withdrawals, which are scaled to align with irrigation withdrawals reported by the United States Geological Survey (Dieter et al., 2018; Maupin et al., 2014). However, they do not provide sub-annual or sub-county estimates of crop water consumption. More recently, Mialyk et al. (2024) provided annual estimates of green and blue CWC globally at 5 arc min resolution from 1990 to 2019. Although they provide estimates at 5 arc min for 175 crops, it's notable that their crop simulation was performed at a much coarser resolution of 30 arc min, and was limited to just 55 crops. Additionally, they provide annual estimates, which means that intra-annual variations in CWC cannot be analyzed.

In this study, we utilize AquaCrop-OS (version 5.0a) (Foster et al., 2017), an open source version of state-of-the-art crop growth model AquaCrop (version 5.0) (Steduto et al., 2009), to estimate the monthly CWC for 13 major irrigated crops in the contiguous US (CONUS) from 1981 to 2019 at a spatial resolution of 2.5 arc min. In addition, we used a simplistic crop model (Marston et al., 2020; Siebert & Döll, 2010) to estimate the monthly CWC for 17 additional crops that currently cannot be readily represented by AquaCrop-OS. A key outcome of this research is the first publicly available time series of monthly green and blue CWC, further partitioned into groundwater and surface water, of the 30 most widely irrigated crops in the CONUS. This data set, which we call MIrAg-US (Modeled Irrigated Agriculture of the United States) (Lamsal & Marston, 2024c), allows us to answer the following research questions: (a) How does crop-specific average CWC vary spatially across the CONUS and monthly across the year? (b) How does crop-specific annual CWC vary in space and time from 1981 to 2019? We also rigorously assessed our CWC estimates against other crop model estimates, government records of water use, and remotely sensed evapotranspiration estimates.

2. Materials and Methods

We estimated the monthly CWC of 13 major irrigated crops (see Table S1 in Supporting Information S1) from 1981 to 2019 at a spatial resolution of 2.5 arc min in the US using the AquaCrop-OS model, which we describe in Section 2.1. These 13 crops represent approximately 69% of total irrigated croplands (USDA, 2019a), and 56% of irrigation use for all crops in 2012 (Marston et al., 2018). Additionally, we estimated the monthly CWC of 17 irrigated crops using a simple crop growth model (Marston et al., 2020; Siebert & Döll, 2010), as crop parameters required to run the AquaCrop-OS model were not available. We describe these steps in Section 2.2. Together, these 30 crops in our study represent approximately 94% of US irrigated cropland (USDA, 2019b) and 95% of irrigation water consumption (Marston et al., 2018). We further divided the blue CWC into groundwater and surface water CWC using county-level water withdrawal data (Dieter et al., 2018; Hutson et al., 2004; Kenny et al., 2009; Maupin et al., 2014; Solley et al., 1988, 1993, 1998) as described in Section 2.3. While the focus of this paper is on the irrigation consumption of actual irrigated croplands, MIrAg-US provides CWC for all grid cells in the CONUS regardless of whether the crop is grown or not. This allows researchers to use this data set to compute volumetric crop water consumption for hypothetical scenarios by combining CWC with hypothetical harvested area data sets. We then computed crop-specific volumetric CWC (VCWC) for each 2.5 arc min grid by multiplying CWC depth with the corresponding harvested area (Lamsal & Marston, 2024a, 2024b) as described in Section 2.4. We note that this VCWC is masked using actual crop growing areas provided by HarvestGRID (Lamsal & Marston, 2024a, 2024b), a gridded data set that provides crop-specific irrigated harvested areas for 30 crops in the US at a spatial resolution of 2.5 arc min from 1981 to 2019. HarvestGRID combines county-level harvested area records from USDA and gridded remotely sensed data products, including the Cropland Data Layer (Han et al., 2012), LANID (Xie et al., 2021), and other land use data sets (Sohl et al., 2014, 2016). We assessed our model output by comparing our CWC estimates with existing data sources including modeled CWC estimates (Chiarelli et al., 2020; Mekonnen & Hoekstra, 2011; Siebert & Döll, 2010), remotely sensed estimates from OpenET (Melton et al., 2022), and irrigation estimates from state and federal agencies (Dieter et al., 2018; Hutson et al., 2004; Kenny et al., 2009; Maupin et al., 2014; Solley et al., 1988, 1993, 1998; USDA, 2014; USDA, 2019a). We describe these intermodal comparisons in Section 2.5. A schematic overview of the development of the data products is shown in Figure 1.

2.1. CWC Using AquaCrop-OS

We use AquaCrop-OS, an open source version of AquaCrop, to estimate CWC for 13 irrigated crops. AquaCrop-OS provides more realistic crop growth and water consumption than the crop models used in many other studies (Chiarelli et al., 2020; Mekonnen & Hoekstra, 2011; Siebert & Döll, 2010), by separating evapotranspiration into evaporation and transpiration, thereby removing the confounding effect of nonproductive water consumption (i.e., evaporation) (Steduto et al., 2009). Additionally, these studies (Chiarelli et al., 2020; Mekonnen & Hoekstra, 2011; Siebert & Döll, 2010) use static crop growth length regardless of climatic conditions, while AquaCrop-OS dynamically adjusts crop growth length using growing degree days. Models commonly used in previous studies provided a more simplistic representation of crop growth, often using seasonal crop coefficients to estimate CWC (Steduto et al., 2009). In contrast, there are some studies (Montoya et al., 2018; Tang et al., 2018; Umair et al., 2017) that use more sophisticated and accurate models, such as DSSAT (Jones et al., 2003) or CropSyst (Malek et al., 2017), to represent crop growth and CWC at the field or watershed scale. However, these models are often more complex and difficult to parameterize at large scales (Foster et al., 2017). AquaCrop-OS balances accuracy, simplicity, and robustness, allowing us to better represent crop growth and CWC than previous large-scale CWC estimates (Steduto et al., 2009; Zhuo et al., 2016), but it is generalizable enough to scale nationally, unlike more complex models.

2.1.1. Crop Model and Inputs

AquaCrop-OS simulates soil water balance and crop growth processes as a function of climate, soil, crop, and management parameters at a daily time step (Figure 1a). AquaCrop is a crop model evolved from Doorenbos and Kassam (1979) that relates relative yield reduction to relative reduction in evapotranspiration (ET). The original model developed by Doorenbos and Kassam (1979) underpins several studies that estimate crop water consumption (e.g. (Chiarelli et al., 2020; Mekonnen & Hoekstra, 2011; Siebert & Döll, 2010)) but AquaCrop improves on this model by removing the confounding effect of the nonproductive consumptive use of water (E) by separating ET into E (evaporation) and Tr (transpiration), estimating Tr using simple canopy growth and senescence model and estimating yield as a function of biomass (Steduto et al., 2009). Since the focus of our study is on the water consumption of major crops in the US over the last four decades, we selected the AquaCrop model because it is water-driven, that is, transpiration is calculated first and translated to biomass using biomass water productivity (Steduto et al., 2009) and it has been widely used in the scientific literature (e.g. (Chukalla et al., 2015; Nouri et al., 2019; Zhuo et al., 2016)). Additionally, we opted for the open-source version, AquaCrop-OS, as it allows parallel execution across multiple CPUs on high-performance computing systems simultaneously, unlike the standard standalone AquaCrop application. We used the default crop parameters provided in the AquaCrop manual (Steduto et al., 2012) for our simulations. These parameters include growing degree days required for various growth stages, temperature thresholds related to pollination and transpiration stresses, root

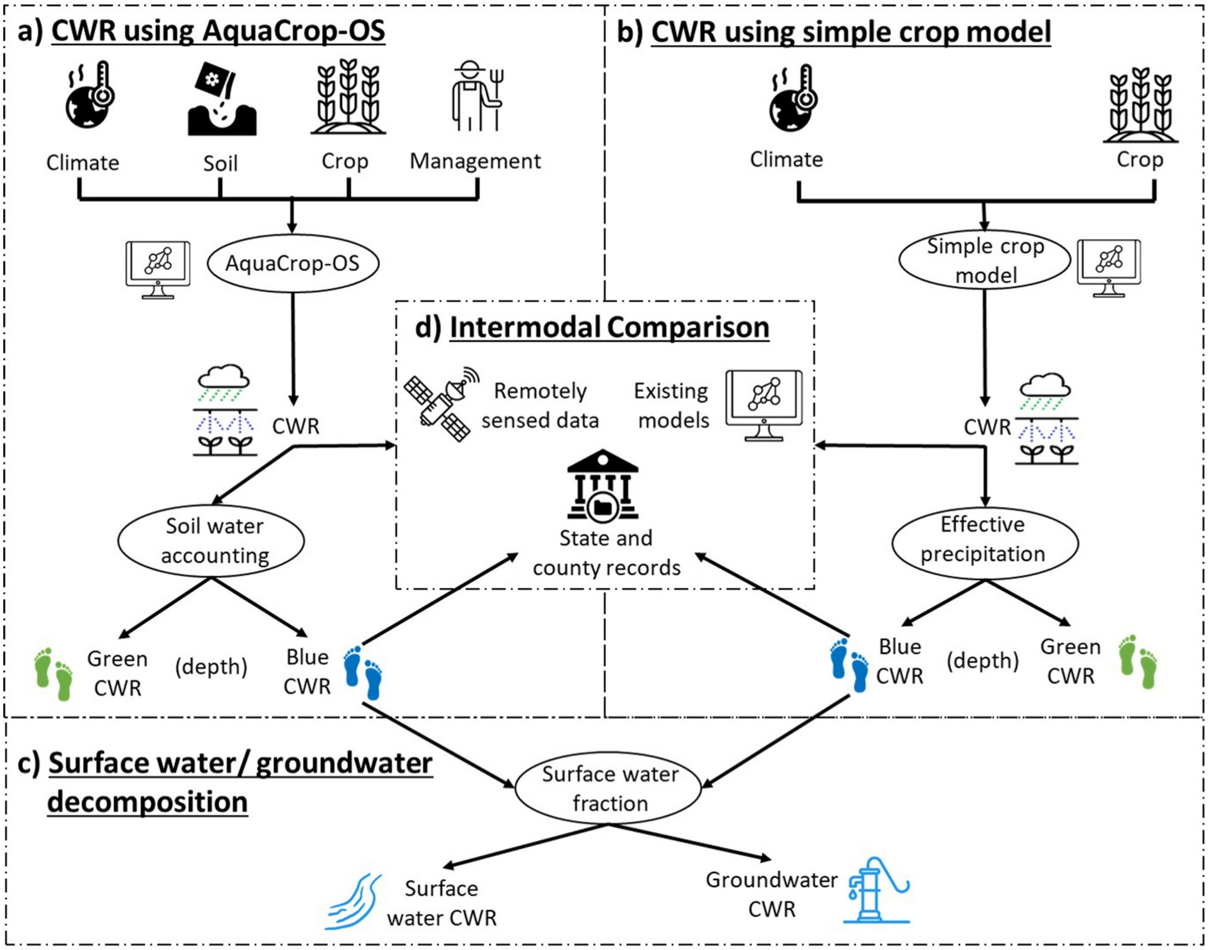

Figure 1. (a) Crop water consumption (CWC) was computed using the AquaCrop-OS (Foster et al., 2017) model. We used detailed climate, soil, crop, and management parameters as input to the model. CWC was partitioned into blue and green components using the soil moisture accounting approach (Chukalla et al., 2015; Hoekstra, 2019; Nouri et al., 2019). (b) CWC was estimated using a simple crop growth model using climate and crop parameters, and the CWC was partitioned into blue and green components using effective precipitation (Marston et al., 2020; Siebert & Döll, 2010). (c) Blue CWC was partitioned into surface water and groundwater CWC using surface water fraction derived from county level water withdrawal data (Dieter et al., 2018; Hutson et al., 2004; Kenny et al., 2009; Maupin et al., 2014; Solley et al., 1988, 1993, 1998). (d) We compared our estimates of total CWC and blue CWC against other modeled estimates, remote sensing estimates, and government records.

water extraction limits, canopy growth coefficients, water productivity values, and soil water depletion thresholds that impact canopy expansion, stomatal closure, pollination, and other processes. More detailed information on model parameters can be found in the AquaCrop manual (Steduto et al., 2012). We note that we use different planting dates than those provided in the default parameters. We describe the source and methods used to obtain planting dates below. The model was parallelized and run on a high-performance computing system. AquaCrop-OS is capable of simulating crop growth in thermal time (i.e., growing degree days (GDD)) and in calendar days (CD). We generally model crop growth using GDD method since the model will dynamically adjust each growing season based on temperature, whereas using CD method relies on predefined growth timelines, regardless of weather conditions. However, we use the CD approach in areas where cold temperatures limit simulation in GDD mode. The initial model output was daily CWC at 2.5 arc min, which we then processed and aggregated to monthly level as described in the following sections.

Daily climatic data (reference evapotranspiration (ETo), precipitation, and minimum and maximum air temperature) were obtained from gridMET (Abatzoglou, 2013) at a spatial resolution of 2.5 arc min. GridMET combines temporally rich data from North American Land Data Assimilation System Phase 2 (Mitchell et al., 2004) and spatially rich data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM (Daly et al., 2008)) to produce a spatially and temporally complete data set (Abatzoglou, 2013).

We obtained soil texture (% of sand, % of clay and % of organic matter) data at multiple depths (0, 5, 15, 30, 60, 100, and 200 cm) from SoilGrids (Hengl et al., 2017) at a spatial resolution of 250 m. We averaged the soil texture data at each depth to 2.5 arc min grids to match the climate data. We assume that the soil characteristics remain temporally static throughout the simulation period.

Crop water consumption estimates are highly sensitive to planting dates; delaying planting by 30 days lead to approximately 20% reduction in total CWC and 40% reduction in blue CWC (Zhuo et al., 2014). Regional or country-level planting dates often used by other studies (Mekonnen & Hoekstra, 2011; Siebert & Döll, 2010) may lead to inaccurate CWC estimates. Therefore, we derived likely planting dates for each crop every year at the 2.5 arc min resolution to match our other data inputs. We derived high-resolution planting dates using crop-specific, sub-monthly progress data for each state obtained from the United States Department of Agriculture (USDA (USDA, n.d.)). The progress data provides the percentage of a crop planted within each state by a given date each year. Missing records were estimated using either interpolated values from neighboring years for the same area or records from the same year but from neighboring states within the same climate region. If planting dates were not available for other years or states, national planting dates were used for less widely grown crops without detailed records. Next, state level planting progress was changed to gridded planting dates by making the following assumptions: (a) crop planting occurs earlier in areas with warmer temperatures than areas in the state with colder temperatures, and (b) crop planting is less likely to occur when soils are wet since this will cause soil compaction and other issues that may reduce crop performance (Sacks et al., 2010; Zuber et al., 2015). We define soils as being too wet to plant when precipitation exceeds 30 mm/week. We note that selecting a different threshold would have a minor impact on the spatial distribution of planting dates across grids within a state, which would, in turn, result in different crop water consumption (CWC) estimates. Still, the sum of grid-scale planting areas each week always match state-level records and if a grid cell is not designated as growing a crop due to rain, it is highly likely to have its planting date in the following week.

Crop and irrigation management parameters in the model include mulching and different irrigation technologies (e.g., furrow, center pivot, drip). Less than 0.4% of US irrigated croplands use any form of mulching (USDA, 2019a); therefore, we do not assign mulching within our model. AquaCrop-OS models irrigation technology by parameterizing wetted surface area and irrigation efficiency. Estimates of irrigation efficiencies and wetted surface area for different irrigation technologies come from FAO (Brouwer et al., 1989) and Chukalla et al. (Chukalla et al. (2015), respectively. We used the crop-specific number of acres irrigated by different irrigation technologies from the Farm and Ranch Irrigation Survey (USDA, 2004; USDA, 2010a, 2010b, 2014) and Irrigation and Water Management Survey (USDA, 2019a) to determine the average irrigation efficiency and percentage of surface area wetted for each crop at the state level. Together, the typical efficiency and wetted surface area of an irrigation technology and the amount of area dedicated to this irrigation technology were combined to provide an area-weighted-average irrigation efficiency and percent of wetted surface area for each crop, state, and year pairing. We note that the assigned irrigation efficiency and wetted surface area is more important when estimating applied water than it is when estimating consumptive water use, the latter being the focus of this study.

Following Nouri et al. (2019), the model was initialized by simulating soil moisture for 2 years preceding our study period. The soil moisture content at the beginning of our study period (i.e., 1981) was thus the final soil moisture at the end of the 2-year model runup period.

2.1.2. Soil Water Balance Accounting

We separated the total CWC into blue and green components by keeping track of incoming and outgoing moisture at the rootzone using a soil water balance accounting framework (Chukalla et al., 2015; Hoekstra, 2019; Nouri et al., 2019). The accounting framework is a physically based tracing method that partitions CWC to blue and green components more accurately than simpler methods such as those that assume irrigation is the difference between the water consumption of rainfed crop production and optimally irrigated crop production (Hoekstra, 2019). Equations 1–5 describe the soil water balance accounting method used in this study, with additional details provided by Hoekstra (2019).

$$S^t_{green} = S^{t-1}_{green} + P^t - SO^t \times \frac{P^t}{P^t + I^t} - \left(D^t + E^t + \mathrm{Tr}^t\right) \times \frac{S^{t-1}_{green}}{S^{t-1}} \quad (1)$$

$$S_{blue}^{t} = S_{blue}^{t-1} + I^{t} - SO^{t} \times \frac{I^{t}}{P^{t} + I^{t}} - \left(D^{t} + E^{t} + \mathrm{Tr}^{t}\right) \times \frac{S_{blue}^{t-1}}{S^{t-1}} \tag{2}$$

$$CWR_{total}^{t} = E^{t} + \mathrm{Tr}^{t} \tag{3}$$

$$CWR_{blue}^{t} = \left(E^{t} + \mathrm{Tr}^{t}\right) \times \frac{S_{blue}^{t}}{S_{green}^{t} + S_{blue}^{t}} \tag{4}$$

$$CWR_{green}^{t} = \left(E^{t} + \mathrm{Tr}^{t}\right) \times \frac{S_{green}^{t}}{S_{green}^{t} + S_{blue}^{t}} \tag{5}$$

where S (soil moisture), P (precipitation), I (irrigation), SO (surface runoff), D (deep percolation), E (evaporation), and Tr (transpiration) on day t. Blue, green, and total water consumption are each tracked according to the index values shown in 1–5. We obtain equation variables as an output from the AquaCrop-OS model at a daily time step. We aggregated daily total CWC and daily blue CWC to the monthly level. The blue water fraction at the monthly level is defined as the ratio of blue CWC and total CWC as shown in Equation 6.

$$Blue\ water\ fraction^{m,y} = \frac{CWR_{blue}^{m,y}}{CWR_{total}^{m,y}} \tag{6}$$

where $blue\ water\ fraction$ refers to the fraction of total CWC that is blue. Index m, y represent month and year.

We assumed that all blue water drains from the soil after the growing season and is not available for the next growing season (i.e., all soil moisture at the beginning of each growing season is from green water). We also assumed that farmers aim to maximize crop yield (English et al., 2002) and that irrigation (i.e., blue water) is applied when rainfall is insufficient to achieve maximum yield. While this is a common assumption across nearly all large-scale crop models (e.g. (Chiarelli et al., 2020; Mekonnen & Hoekstra, 2011; Siebert & Döll, 2010)), individual irrigators may apply less (deficit irrigation) or more irrigation than the optimal. Without detailed metered records of irrigation and field measurements of actual crop water demand, we cannot assess whether over- or under-irrigation is more common, though evidence exists that both occur (e.g. (Deines et al., 2019; USDA, 2019a)). We reemphasize that this study deals with crop water consumption, which may differ from actual crop water application. This potential discrepancy is because (a) applied irrigation is greater than irrigation water transpired by the crop since nonproductive evaporation and runoff occur and (b) irrigation is not only a function of climate, soil, and crop parameters but also the discretion of farmers, which varies and is unknown. In our model, irrigation is triggered when soil moisture is 70% of plant available water, which is measure of soil moisture within the root zone.

2.2. CWC Using Simple Crop Model

We used a simple crop growth model (Marston et al., 2020; Siebert & Döll, 2010) to estimate CWC for 17 irrigated crops. We acknowledge several limitations of this model compared to the AquaCrop-OS model. For instance, this simple model uses a static crop growth cycle to represent crop development. Once the crop is planted, it is assumed to progress through various developmental stages at fixed time intervals, irrespective of weather conditions. In contrast, the AquaCrop-OS model dynamically adjusts the length of the growing season based on growing degree days, which are influenced by temperature and crop type. We obtained planting dates using USDA plant progress data as described earlier in Section 2.1.1. The length of the growing season was obtained using FAO (Allen et al., 1998) and CUP + model (Orange et al., 2003). We partitioned the growing season for each crop into four crop developmental stages (initial, developmental, middle, and late), each with their corresponding crop coefficients (kc) following Allen et al. (1998). We then calculated daily CWC as the product of reference evapotranspiration (ETo) and crop coefficient (kc). We obtained daily ETo from gridMET while kc was obtained using crop coefficient curves derived from FAO (Allen et al., 1998) and the CUP + model (Orange et al., 2003). For alfalfa, which has multiple growth cycles in a single year, we assumed that the growing period started on the first day of the year where temperatures remained above −4 degree Celsius in the first half of the year and ended on last day of the year where temperatures consistently fell below −4 degree Celsius in the second half of the year (Allen et al., 1998; Ruess et al., 2023). Alfalfa was assumed to grow all year where temperatures never fell below this temperature threshold. We then constructed a coefficient curve for alfalfa using the length of developmental stages from FAO. We note that the developmental stages for the first growth cycle are longer than those for subsequent cycles. Additionally, because we lack sufficient information to identify the initial year of planting, we assume that alfalfa is replanted annually to maintain water use comparability across years. We acknowledge that this assumption is a limitation of our study, as it may not accurately reflect real-world planting practices and could influence the estimated water use for alfalfa. We assumed that the CWC for alfalfa and other hay are similar. We partitioned the total CWC into green and blue components assuming that irrigation is applied when crop demand exceeds effective precipitation (Marston et al., 2020). We used USDA Soil Conservation Service (Kent, 1968) method to compute effective precipitation, with daily precipitation averaged over a moving 10 days window to account for soil moisture storage (Marston et al., 2020; Siebert & Döll, 2010). The daily precipitation values were obtained from gridMET.

2.3. Surface Water/Groundwater Decomposition

The blue CWC was further divided into surface water and groundwater components by using the surface water fraction derived from county-level irrigation withdrawal data (Dieter et al., 2018; Hutson et al., 2004; Kenny et al., 2009; Maupin et al., 2014; Solley et al., 1988, 1993, 1998), as shown in Equation 7. If the surface water fraction was unavailable for a year, we used the same fraction from the nearest year. We assume that the relative proportion of groundwater and surface water consumption is similar to the proportion of total irrigation withdrawals from groundwater and surface water within a county. Furthermore, this approach assumes that each crop relies on groundwater and surface water in the same proportion throughout a county and year, which may not always be the case. Thus, we caution against making crop-specific conclusions on surface water or groundwater consumption within a single grid cell. The surface water CWC is calculated by taking the product of blue CWC and the surface water fraction, as shown in Equation 8. The difference between blue CWC and surface water CWC is the groundwater CWC, as shown in Equation 9.

$$surface\ water\ fraction^{y} = \frac{Withdrawal_{SW}^{y}}{Withdrawal_{SW}^{y} + Withdrawal_{GW}^{y}} \tag{7}$$

$$CWR_{SW}^{m,y} = CWR_{blue}^{m,y} \times surface\ water\ fraction^{y} \tag{8}$$

$$CWR_{GW}^{m,y} = CWR_{blue}^{m,y} - CWR_{SW}^{m,y} \tag{9}$$

where, *withdrawal* and *surface water fraction* represent annual county-level withdrawal values from USGS and fraction of blue CWC that is surface water, respectively. Index *SW* and *GW* represent surface water and groundwater.

2.4. Volumetric CWC

We computed volumetric CWC (VCWC) by multiplying CWC depth by the corresponding irrigated crop harvested area (Area) using Equation 10. We obtained annual irrigated harvested area for these 30 crops from Lamsal and Marston (2024a); Lamsal and Marston (2024b) at 2.5 arc min.

$$VCWR_{type}^{m,y} = CWR_{type}^{m,y} \times Area^{y} \tag{10}$$

where, *type* represents type of CWC which can be total, blue, surface water or groundwater.

2.5. Intermodal Comparison

We assessed MIrAg-US by comparing our total CWC with published estimates of US CWC (Chiarelli et al., 2020; Mekonnen & Hoekstra, 2011; Siebert & Döll, 2010) and remotely sensed evapotranspiration estimates from OpenET (Melton et al., 2022). In addition, we compared our blue CWC to applied irrigation estimates from state and federal agencies (Dieter et al., 2018; Hutson et al., 2004; Kenny et al., 2009; Maupin et al., 2014; Solley et al., 1988, 1993, 1998; USDA, 2014; USDA, 2019a), which we describe in detail in Section 2.5.3. We only compared our estimates against these original data products; derivative products of one of these data sets were not

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Table 1
List of Data Sources, Spatial and Temporal Units of Comparison, Number of Crops Compared, and Other Metrics Used for Comparison

Source	Temporal unit	Spatial unit	Crop (# of crops compared)	Unit	Metric	Type
Mekonnen and Hoekstra (Mekonnen & Hoekstra, 2011)	Average of 1996–2005	5 arc min	Specific crops (25)	Depth	Consumption	Total
Siebert and Döll (Siebert & Döll, 2010)	Average of 1998–2002	5 arc min	Specific crops (17)	Depth	Consumption	Total
WATNEEDS (Chiarelli et al., 2020)	2000 and 2016	5 arc min	Specific crops (17)	Depth	Consumption	Total
FRIS (USDA, 2014; USDA, 2019a)	2012 and 2017	State	Specific crops (12)	Depth	Applied water	Blue
USGS (Solley et al., 1988; Solley et al., 1993, 1998; Hutson et al., 2004; Kenny et al., 2009; Maupin et al., 2014; Dieter et al., 2018)	1985, 1990,… 2015	County	Aggregated	Volume	Withdrawal	Blue
OpenET (Melton et al., 2022)	2016–2022	30 m	Specific crops (30)	Depth	Consumption	Total
MIrAg-US (Lamsal & Marston, 2024c)	1981–2019	2.5 arc min	Specific crops (30)	Depth and volume	Consumption	Total

Note. We note that our study, MIrAg-US, provides crop water consumption (CWC) estimates for 30 crops at the monthly level from 1981 to 2019 at a spatial resolution of 2.5 arc min. We perform several data transformations as required before comparing with other data sets.

compared against our estimates (e.g., Marston et al. (2018) is based on Mekonnen and Hoekstra (2011); Ruess et al. (2024) is scaled to match USGS (Dieter et al., 2018; Maupin et al., 2014)).

Table 1 lists references for each comparison data set, their temporal and spatial resolution and coverage, and the variables used for comparison. Since our data set is generally at a finer spatial and temporal resolution and covers a longer time period than most studies, we resolved MIrAg-US and other data products to the same spatial scale and temporal resolution/period before comparison. Other data transformations were required for some data products (described in more detail below) to more accurately compare different data products.

Our study is unique in that most large-scale crop models do not make such comprehensive comparisons against other existing models and/or against other available data. These comparisons are made to demonstrate the agreement, or lack thereof, among existing modeling approaches. Our models, as well as all other national US crop irrigation models, cannot be fully validated since we lack robust validation data - namely, actual ET and irrigation measurements - for the US. Nonetheless, MIrAg-US is generally in agreement with other data products.

2.5.1. Comparison With Existing Models

We performed a crop-by-crop, grid-by-grid comparison of total CWC from our model with total CWC from three existing models (Chiarelli et al., 2020; Mekonnen & Hoekstra, 2011; Siebert & Döll, 2010). We resampled the existing models to 2.5 arc min from 5 arc min by assuming that the outputs are uniform over the entire 5 arc min region. We aggregated our monthly results to produce yearly estimates and compared our results to the years for which data was available for these studies, as detailed in Table 1.

2.5.2. Comparison With OpenET

To further evaluate the accuracy of our model, we performed a comparison with the OpenET data product. OpenET provides daily estimates of actual evapotranspiration (ETa) in the western US from 2016 onward using multiple models that rely on remote sensing products (Gorelick et al., 2017). Most of the models that constitute the OpenET ensemble ET are based on either the full or simplified surface energy balance approach. Though the individual models can vary significantly between themselves, utilizing diverse ET models improves reliability by overcoming limitations of any single model (Melton et al., 2022). Still, the mean absolute error (MAE) of OpenET's mean ensemble ET was 0.74 mm/day when compared to flux towers (21.8% error), with individual models reporting MAE values significantly higher (Melton et al., 2022).

We accessed the OpenET data in Google Earth Engine, and applied an agricultural mask using Cropland Data Layer (Han et al., 2012), and irrigation mask using Landsat-based Irrigation Data set (Xie et al., 2021) as OpenET provides ETa estimates for all land parcels (including non-irrigated lands and non-agricultural lands).

Additionally, as MIrAg-US estimates CWC for the crop growing season, we restricted the OpenET data to the same temporal range, excluding ET occurring outside of the growing season. We then calculated the county-level average ETa (mm) from OpenET for each irrigated crop during the growing season and compared it with the corresponding estimate from our model. We note that OpenET provides actual ET estimates constrained by water availability, whereas our modeled estimates, as well as the other crop models we compare against, assume no such limitation. We make comparisons at the county level because of computational limitations; the number of aggregation limits in Google Earth Engine did not allow us to compare at a finer spatial resolution.

2.5.3. Comparison With County and State Records

We compared our results with county-level irrigation water withdrawal volumes reported every five years from 1985 to 2015 by the United States Geological Survey (USGS) (Dieter et al., 2018; Hutson et al., 2004; Kenny et al., 2009; Maupin et al., 2014; Solley et al., 1988, 1993, 1998). The USGS compiles estimates of total irrigation withdrawals (i.e., not crop specific) at the county-level provided by each state. Rarely are irrigation withdrawals metered and states employ a variety of different, often undisclosed, methods for estimating irrigation withdrawals (Marston et al., 2022). Methods employed by each state to estimate irrigation withdrawals vary in their degree of sophistication and accuracy. Nonetheless, this is one of the most widely cited products that USGS publishes, indicating its importance to the scientific community.

To compare MIrAg-US to USGS irrigation estimates, we summed all volumetric blue CWC for all crops within each county for each year matching the USGS reporting years. We divided the aggregated volumetric blue CWC by the county's average irrigation efficiency for the given year to obtain comparable irrigation withdrawal values. The average irrigation efficiency for each county was calculated by taking the weighted average of county-level irrigated area for micro, surface, and sprinkler irrigation technologies. Instead of calculating crop-specific, state-level irrigation efficiency as described in the irrigation management parameter above, we compute irrigation efficiency at the county level here since these values come from the USGS data source we are comparing against, thus offering a more direct comparison.

We also compared our model estimates with crop-specific applied irrigation depth records from the Farm and Ranch Irrigation Survey (USDA, 2014) for 2013 and the Irrigation and Water Management Survey (USDA, 2019a) for 2018. These estimates come from farmer surveys; however, it is not always clear the method used by farmers to estimate their irrigation application since metering is uncommon in the sector. Though these data specify the depth of irrigation applied by crop type and irrigation technology, values are only reported at the state level. Therefore, we must aggregate our results to the state level as well. We computed the weighted average blue CWC depth for each state by taking the product of blue CWC and harvested crop area for each grid cell within the state and dividing the resultant product by the total area of that crop in the state. Crop water applied by each irrigation technology was obtained by dividing the weighted average blue CWC by the efficiency of that irrigation technology.

3. Results

We computed blue, green, and total CWC for 30 major irrigated crops at the monthly level from 1981 to 2019 using crop models at the spatial resolution of 2.5 arc min for the CONUS. Here, we first present the average monthly and annual CWC (3.(a), and annual CWC (3.(b) for irrigated crop production across the CONUS. Finally, we show how our model estimates compare against other existing estimates in Section 3.3.

3.1. Average Monthly and Annual Crop Water Consumption Across the US

The average annual total CWC for irrigated production of 30 major crops in the US amounted to 154.3 km^3, with approximately 70% (107.9 km^3) derived from blue water sources (see Table S2 in Supporting Information S1). The remaining 30%, equivalent to 46.4 km^3, was sourced from green water. The six primary crops—alfalfa (24.8 km^3), corn (16.6 km^3), other hay (12.4 km^3), cotton (11.9 km^3), soybean (9.1 km^3), and winter wheat (5.3 km^3)—constituted roughly three-quarters of the average annual blue CWC. One of these six crops consumed the largest share of blue water in more than 90% of the counties in the CONUS (Figure S1 in Supporting Information S1). Corn ranked as the most or second-most irrigated crop by total volume in nearly half of these counties. Regionally, corn and soybeans were the dominant crop in the eastern states, while alfalfa and other hay were more dominant in the western states.

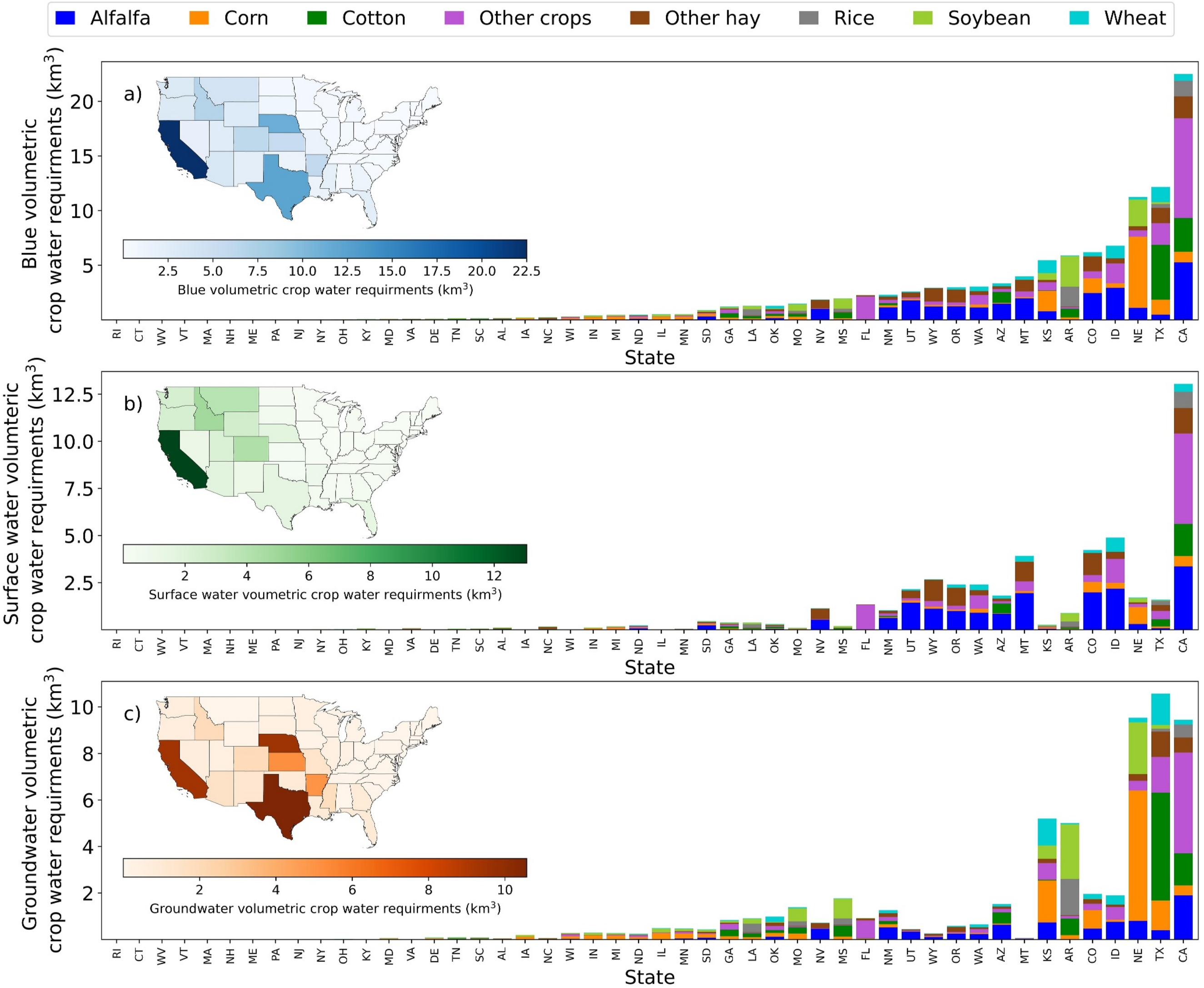

Figure 2. The average annual (a) blue volumetric crop water consumption (VCWC; km^3), (b) surface water VCWC, and (c) groundwater VCWC for major irrigated crops for each state in the CONUS.

California had the highest average annual blue VCWC among the states, totaling approximately 22.5 km^3 as shown in Figure 2. This accounted for over 20% of the average annual blue VCWC across the CONUS, despite California comprising only about 5% of the CONUS land area. Approximately 60% of the average annual blue VCWC in California came from surface water. Collectively, alfalfa, cotton, grapes, almonds, other hay, and rice accounted for more than three quarters (17.4 km^3) of California's blue VCWC. Other states with significant average annual blue VCWC included Texas, Nebraska, Idaho, Colorado, Arkansas, and Kansas, as shown in Figure 2. Cotton consumed the most blue water in Texas, representing more than two-fifths of the average annual blue VCWC. Corn and soybeans were the two major crops in Nebraska, accounting for approximately 58% and 22% of the average annual blue VCWC, respectively. Soybeans, rice, and cotton accounted for approximately 2.8 km^3, 1.8 km^3, and 0.8 km^3 of average annual blue CWC, respectively in Arkansas, representing more than 90% of the state's average annual blue VCWC. Notably, about 90% of the average annual blue CWC came from groundwater sources in Texas, Kansas, and Nebraska.

Figure 3 shows the distribution of the average annual blue VCWC, surface water VCWC, and groundwater VCWC for irrigated crops for each 2.5 arc min grid in the CONUS. There are notable concentrations of blue VCWC, more specifically groundwater VCWC, around major aquifers such as the Central Valley Aquifer, High Plains Aquifer, and Mississippi Embayment Aquifer. The irrigated croplands overlaying these three aquifers

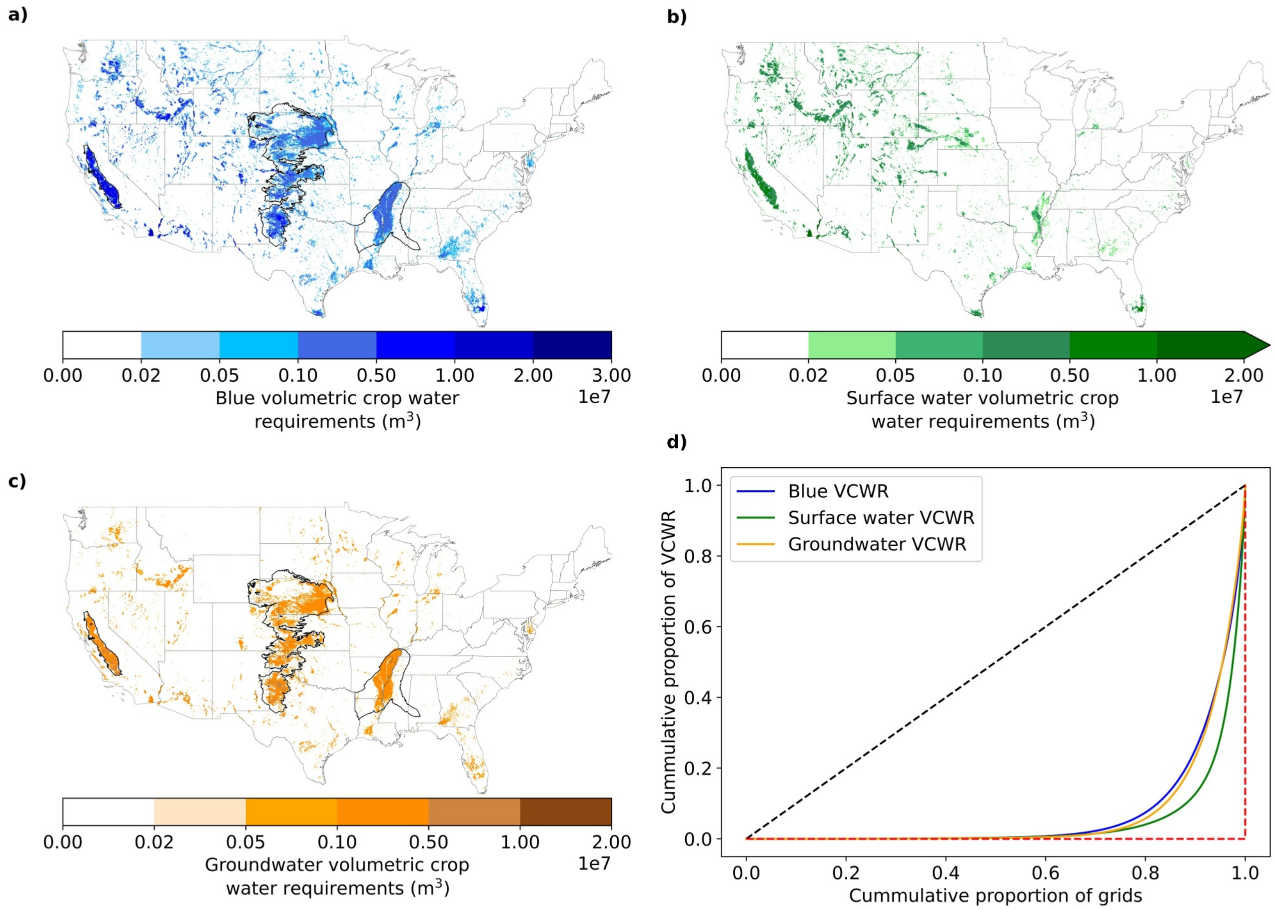

Figure 3. Average (1981–2019) annual (a) blue volumetric crop water consumption (VCWC), (b) surface water VCWC, (c) groundwater VCWC, and (d) cumulative proportion of VCWC accounted for by cumulative proportion of 2.5 arc min grid cells across the contiguous United States. The black dotted line in panel (d) shows hypothetical perfect equality (all grids account for equal amounts of VCWC), and the red dotted line shows hypothetical perfect inequality (a single grid accounts for all VCWC). We are presenting the results at the grid level for visual purposes. We caution against drawing conclusions on a crop's water source for individual grid cells.

account for less than 10% of CONUS land area but make up 54.1 km^3 of blue VCWC (50.2%) and 42.0 km^3 of groundwater VCWC (69.2%). There are notable concentrations of surface water VCWC in California, and along major rivers such as Snake River, Yellowstone River, Missouri River, and Platte River.

Figure 3d shows the Lorenz curve (Lorenz, 1905), illustrating the relationship between the cumulative proportion of land area (represented by 2.5 arc min grid cells; *x*-axis) and the cumulative proportion of VCWC associated with the land area (*y*-axis). We find that just 10% of irrigated croplands account for over 90% of irrigation volume (i.e., blue VCWC). Additionally, we computed the Gini index to quantify the variability in VCWC across irrigated croplands in the US. The Gini index, a measure of statistical dispersion or inequality, ranges from zero (perfect equality, i.e., all grid cells account for equal amounts of VCWC) to one (perfect inequality, i.e., only one grid cell accounts for all VCWC). Our findings show the Gini index for blue VCWC, surface water VCWC, and groundwater VCWC in the CONUS is equal to 0.93, 0.95, and 0.94, respectively, indicating large inequality in VCWC across the grid cells. In other words, a small portion of land area is responsible for the vast majority of US water consumption. The disproportionate water consumption, which serves as a proxy for crop production, highlights the vulnerability of these areas to disruptions that could have significant implications for food security. Furthermore, regions with high water consumption are likely to face challenges related to local water scarcity and potential environmental degradation.

Figure 4 shows average monthly blue CWC for major irrigated crops in the CONUS. The majority of the CWC is from April to October, which accounted for more than 90% of average monthly blue CWC. The CWC in July was the highest, requiring more than 20% of annual blue CWC. Nationally, alfalfa consumes the most blue water

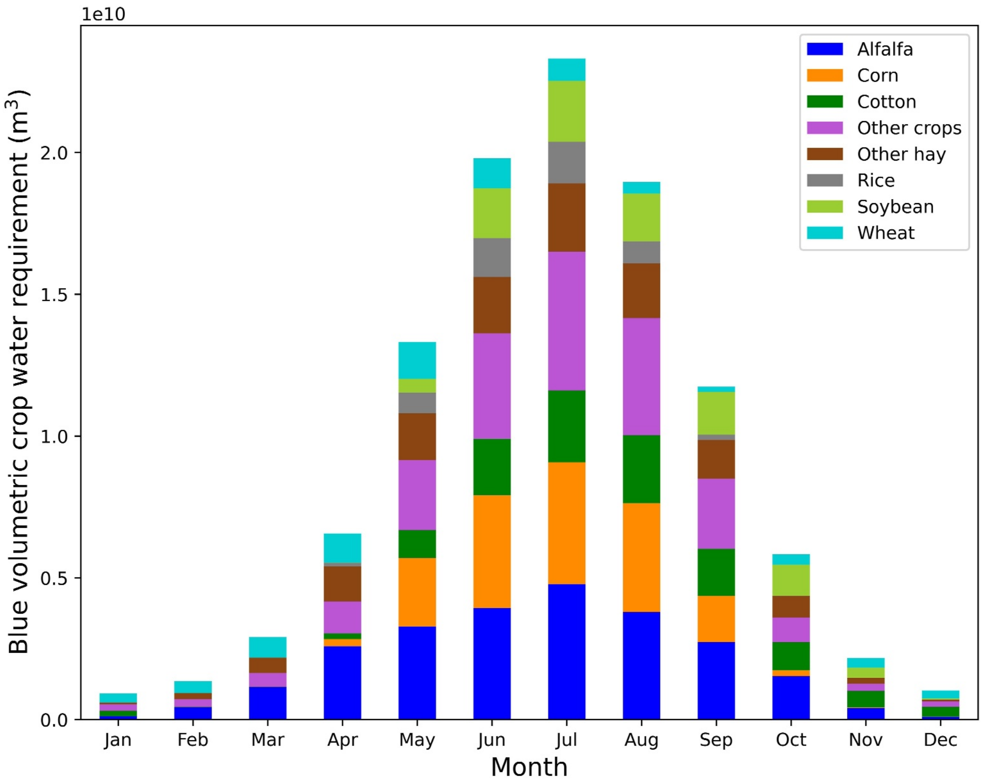

Figure 4. Average (1981–2019) monthly volumetric blue crop water consumption (VCWC; m^3) for major crops in the contiguous United States.

7 months a year, while corn is the most irrigated crop in June and August, and winter wheat is the most irrigated crop in January. Cotton is the most irrigated crop in November and December due to late harvesting that can extend to January in Texas (USDA, 2010a, 2010b), the largest consumer of blue VCWC for cotton.

3.2. Annual Crop Water Consumption Across the US

The annual blue VCWC of irrigated crop production in the US ranged from 93.1 km^3 in 1983 to 130.1 km^3 in 2012 as shown in Figure 5. The annual blue VCWC was equal to 116.3 km^3 in 1981, which decreased by approximately 17.5%–95.9 km^3 in 2019. This reduction in blue VCWC can be partially attributed to a 6.2% decline in irrigated harvested area between 1981 and 2019. The remaining decrease in blue VCWC may be due to several other factors, including changes in climatic conditions that reduce the need for blue water, the relocation of crop cultivation to regions with lower blue water consumption, and a shift toward growing crops that consume less blue water. Surface water VCWC decreased by approximately 40%, whereas groundwater VCWC increased by approximately 7% between 1981 and 2019. We observe a sudden drop in surface water VCWC from 2013 onwards. This decrease in surface water is due to an increase in reliance on groundwater sources during droughts in California (Marston & Konar, 2017), which accounted for the largest blue VCWC and surface water VCWC.

Crop-specific VCWRs have changed much more, in percentage terms, than the VCWRs for all the crops combined. The annual blue VCWC for alfalfa decreased by approximately 6.0 km^3 (23%), and the total irrigated harvested area decreased by approximately 10% between 1981 and 2019. This decline in blue VCWC is due to the 6.3 km^3 decline in annual surface water VCWC and 0.3 km^3 increase in annual groundwater VCWC. During the same period, both the annual blue VCWC and the irrigated harvested area for winter wheat decreased by more than three fifths. In contrast, the two most widely grown crops, corn and soybeans, showed an increasing trend in annual blue VCWC. Corn accounted for approximately 15.2 km^3 of annual blue VCWC in 1981. The annual blue VCWC increased by approximately 13%–17.2 km^3 in 2019, while the total irrigated harvested area increased by approximately 30%. This increase in blue VCWC for corn is due to an increase in groundwater VCWC which increased by approximately 2.8 km^3 between 1981 and 2019. Similarly, annual blue VCWC for soybeans more

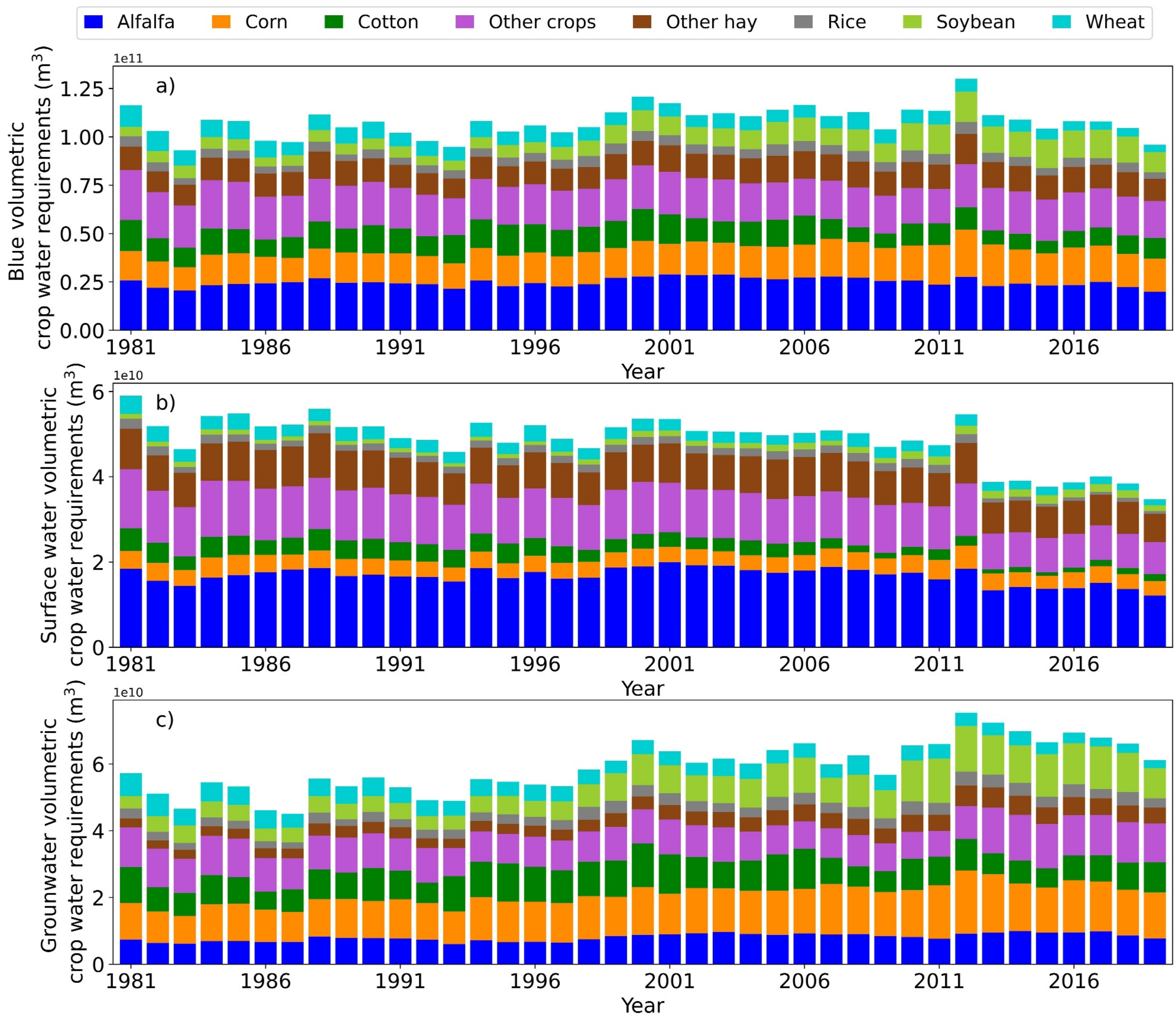

Figure 5. Time-series showing annual (a) blue, (b) surface water, and (c) groundwater CWC from 1981 to 2019 for 30 major irrigated crops in the CONUS.

than doubled from 4.9 km^3 in 1981 to 10.4 km^3 by 2019. More than 95% of this increase in blue VCWC for soybeans is due to an increase in groundwater VCWC.

Figure 6 illustrates the annual time-series data depicting the distribution of blue, green, and total VCWC of irrigated croplands for each state in the CONUS. In western states, such as Washington, Oregon, California, Utah, Arizona, and Nevada, the overwhelming majority of total VCWC comes from blue water. In contrast, in the eastern states, approximately half of the total VCWC of irrigated croplands is blue, with the remaining half being green. Several states in the west exhibit a declining trend in VCWC, while states situated in the central region show an increasing trend. For instance, between 1981 and 2019, Missouri, Arkansas, Mississippi, and Indiana show nearly a doubling of VCWC, corresponding with a similar increase in irrigated crop area. Several states in the east show large percent changes in the VCWC of irrigated croplands, but these states had relatively little irrigated croplands and associated blue VCWC to begin with.

Changes in cropping patterns dramatically changed VCWC at the state level. In 1981, the annual blue VCWC for California was 27.5 km^3, which decreased by approximately 34% to 18.2 km^3 in 2019, as shown in Figure 6. During the same period, the harvested irrigated area decreased by approximately 41% in California, which suggests that farmers shifted to more water intensive crops or irrigated more intensely since the decrease in irrigated area outpaced the decrease in irrigation demand. The blue VCWC for alfalfa and cotton decreased by

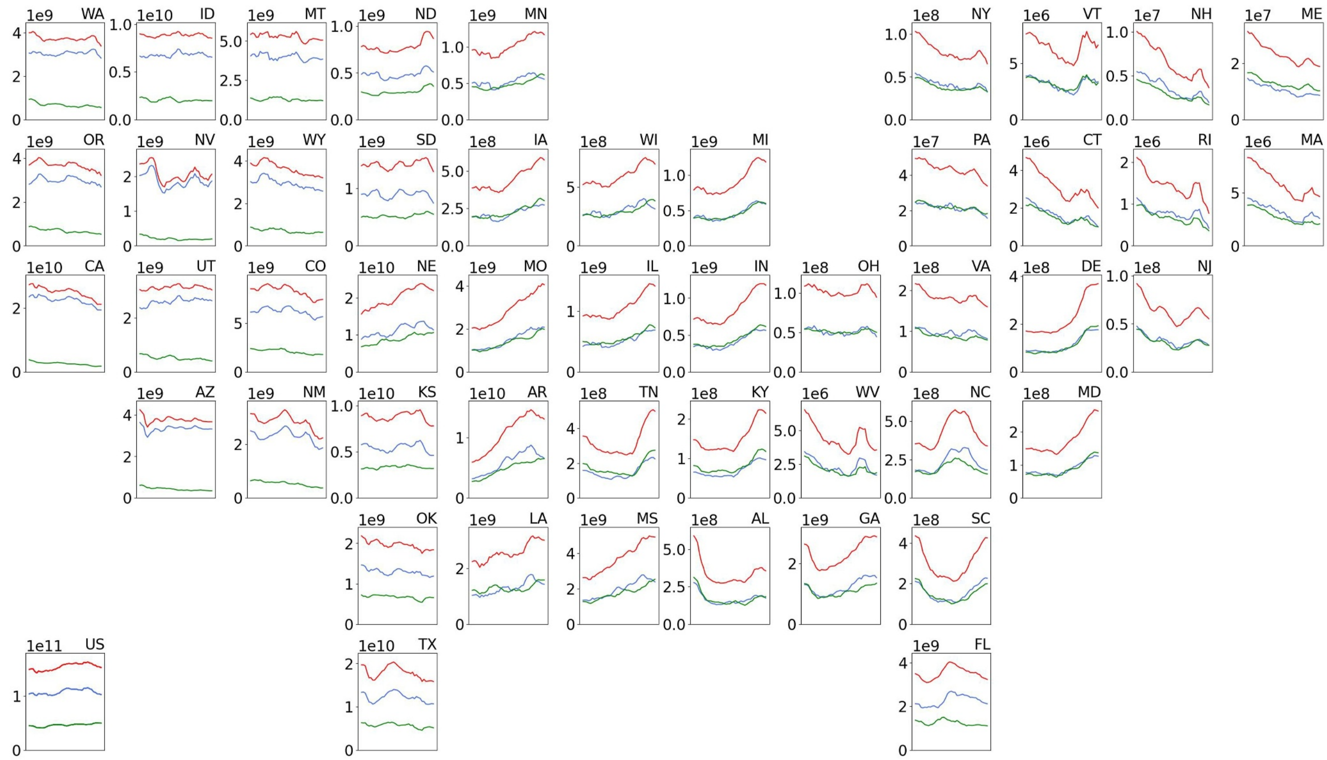

Figure 6. Time-series showing annual blue (blue line), green (green line), and total (red line) CWC from 1981 to 2019 for each state in the CONUS. Here, the 5-year rolling average is shown for visual clarity.

approximately 48% and 83%, respectively, while the blue VCWC for almonds increased by approximately 160% between 1981 and 2019. The percentage changes in irrigated harvested area for each of these crops were similar to the changes in VCWC. Soybeans in Nebraska accounted for 0.57 km^3 of annual blue VCWC in 1981, which increased by approximately 398% to 2.8 km^3 by 2019. The annual blue VCWC for Arkansas increased from 3.1 km^3 in 1981 to 5.7 km^3 in 2019. These increments in the annual blue VCWC can be attributed to soybeans and cotton, which have increased by approximately 342% and 322%, respectively, between 1981 and 2019.

3.3. Intermodal Comparisons

We find that our CWC estimates are generally in agreement with other data sources; however, the degree of agreement varies depending on crop type, models being compared, and geographical region. As shown by the hexagonal binning plot in Figure 7, our model estimates of total CWC align with existing models: 67%, 91%, 74%, and 89% of our estimates are within 50% of estimates from Siebert and Döll (2010), Mekonnen and Hoekstra (2011), WATNEEDS (Chiarelli et al., 2020), and OpenET (Melton et al., 2022), respectively. Most data points lie close to the 1:1 line, indicating strong agreement between our model estimates and those of other studies. Almost all the points are within the 1:2 line and 2:1 line, indicating general to more limited agreement between our model and other studies. On average, less than 10% of our estimates fall below 1:2 line or above the 2:1 line when compared to each of the four different estimates of crop ET. We observe some heavy density points away from the 1:1 line (Figures 7b and 7c); this is largely due to biases in crop-specific estimates rather than biases related to location. For most crops, our estimates closely align with that of Mekonnen and Hoekstra (2011). For instance, a significant percentage of our estimates are within 25% of estimates from Mekonnen and Hoekstra (2011) for cotton (80%), corn (70%), barley (80%), sugarbeets (95%), and soybeans (98%). Our CWC estimates for potatoes are lower than other studies, which can be explained by the relatively shorter growing season used in our study. Our shorter growing period reflects the actual conditions where potatoes are grown instead of general crop calendars used in other studies. For other crops, our estimates better align with estimates from WATNEEDS. For instance, less than 15% of our estimates are within 25% of Mekonnen and Hoekstra (2011) for rice, whereas more than 75% of our estimates are within 25% of WATNEEDS. Similarly, only about 40% of our

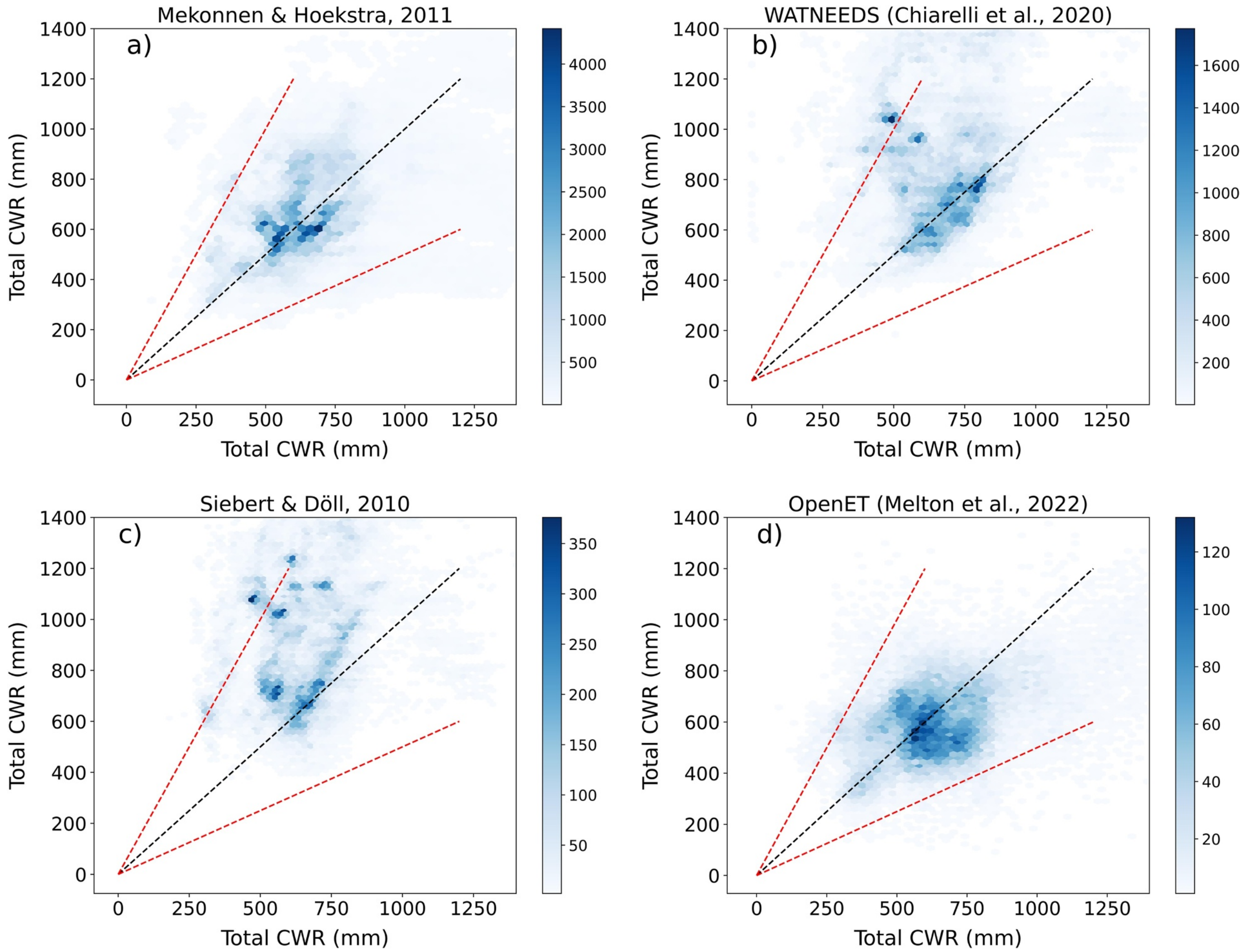

Figure 7. Crop-specific comparisons of total CWC from current study (*x*-axis) with previous estimates (*y*-axis) form (a) Mekonnen and Hoekstra (2011), (b) WATNEEDS (Chiarelli et al., 2020), (c) Siebert and Döll (2010), and (d) OpenET (Melton et al., 2022). The count of points is represented by the colorbar on the right of each panel, where higher density of points is shown by darker shades of blue. Dotted black lines represent 1:1 line and dotted red lines represent 1:2 and 2:1 lines. It is important to note that the color bars have different data ranges across the panels to preserve the visibility of details, especially in panels with fewer data points. We are presenting the results at the grid level for visual purposes. We caution against drawing conclusions on a crop's water source for individual grid cells.

estimates are within 25% of Mekonnen and Hoekstra (2011) for sunflowers, whereas almost 80% of our estimates are within 25% of estimates from WATNEEDS. Crop-specific maps showing percentage difference between current estimates and estimates from other process-based models are shown in Figures S2–S27 in Supporting Information S1.

Methodological differences, as well as differences in input parameters, explain instances of disparities between our results and modeled outputs reported in previous studies. For instance, we use climate data including daily reference evapotranspiration from gridMET, while Mekonnen and Hoekstra (2011) use monthly long-term average reference evapotranspiration from FAO. Similarly, WATNEEDS model uses monthly reference evapotranspiration from Harris et al. (2014). Moreover, these previous studies generally relied on global input data sets that are less detailed in either spatial or temporal resolution, or both, and often less accurate compared to the US-specific input data used in our study. Notably, these studies (Chiarelli et al., 2020; Mekonnen & Hoekstra, 2011; Siebert & Döll, 2010) utilized MIRCA2000 (Portmann et al., 2010) for irrigated harvested area, which disaggregates state-level USDA harvested area data into 5 arc-minute resolution. In contrast, our study employs HarvestGRID, which uses county-level USDA harvested area data, along with 30-m resolution irrigated crop area, to achieve a finer resolution of 2.5 arc min. By relying on finer administrative units (county-level) rather than coarser ones (state-level), errors are confined to smaller regions, improving spatial accuracy. Additionally, the WATNEEDS model (Chiarelli et al., 2020) uses the same harvested area for both 2000 and 2016, further limiting

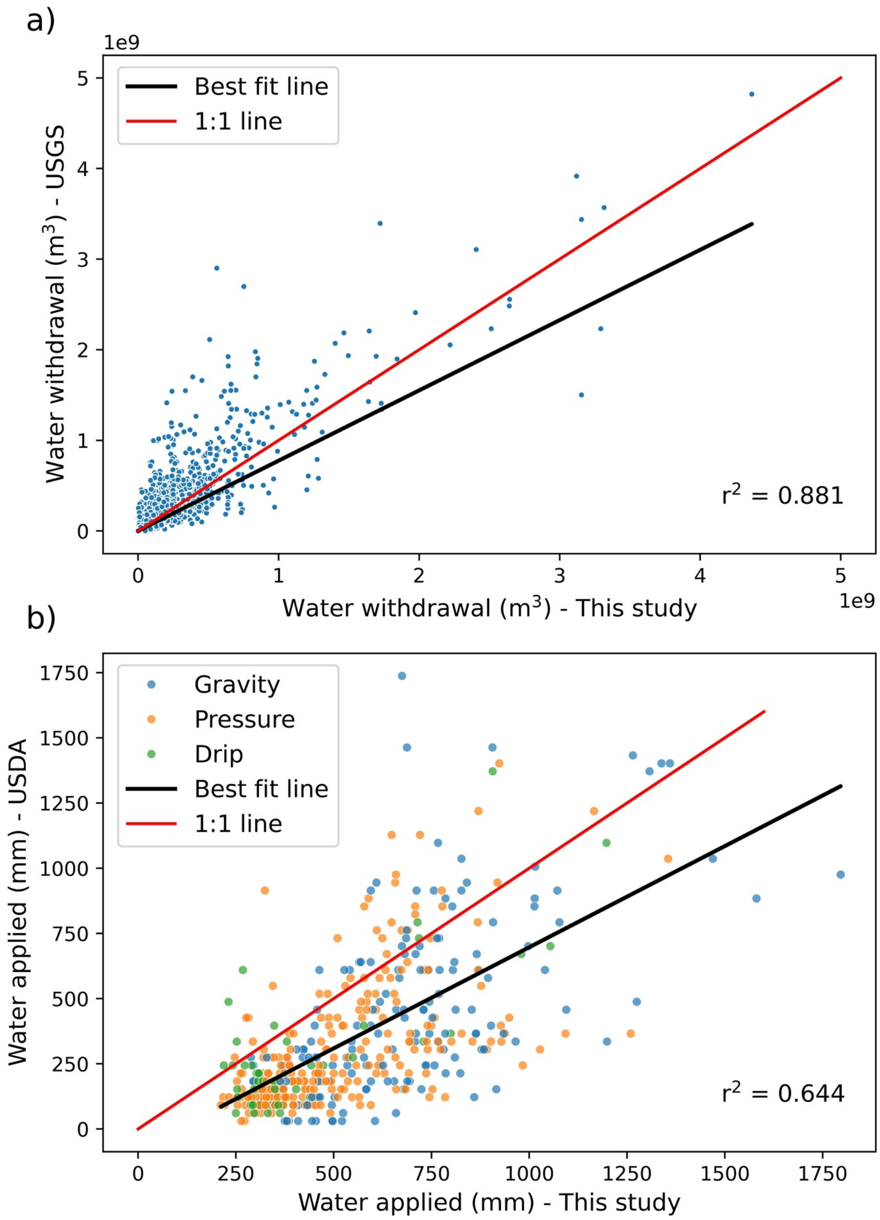

Figure 8. (a) Scatter plot comparing water withdrawals for each county based on the current study (x-axis) and USGS (Dieter et al., 2018; Hutson et al., 2004; Kenny et al., 2009; Maupin et al., 2014; Solley et al., 1988, 1993, 1998) water use census estimates of irrigation withdrawals (y-axis). (b) Scatter plot showing the relationship between water depth applied for each crop based on current study (x-axis) and USDA estimates (USDA, 2014; USDA, 2019a) (y-axis) for three different irrigation technologies. The red line shows the 1:1 line and the black line is the line of best fit in both panels.

its temporal specificity, while we use a time-series of harvested area records from HarvestGRID. Zhuo et al. (2014) quantified uncertainties in CWC estimates stemming from uncertainties in various input parameters. For instance, a 20% increase in ETo led to total CWC increases of 100%, 60%, 50%, and 40% for soybeans, wheat, corn, and rice, respectively. Similarly, they found that delaying planting by 30 days resulted in a reduction of total CWC by almost 35% in corn, while an increase of about 20% was observed in soybeans. This is why our downscaled planting dates derived from sub-monthly observations distinguish our work from other studies that use regional or country-level planting dates. Overall, Zhuo et al. (2014) show that CWC estimates are highly sensitive to input parameters, and could potentially explain differences in estimates from the different studies.

Figure 8a shows the comparison of county-level water withdrawal estimates from our study with the withdrawals estimated by USGS. We observe that our estimates align ($r^2 = 0.88$) closely with USGS estimates. However, the relative variance is larger when a county's irrigation withdrawals are small. Figure 8b shows the comparison of crop-specific water depths for the three different irrigation technologies reported by the USDA, showing reasonable agreement ($r^2 = 0.64$). We note that our estimates are bounded between USDA and USGS estimates, with our estimates often larger than those of USDA, while generally less than those of USGS. Again, notable distinctions in estimation methods and contrast data inputs likely explain much of the differences found between the data sets. Moreover, several transformations including spatial scaling, temporal scaling and averaging, changing consumption to withdrawals, were needed before any meaningful comparisons could be made, which may have made differences between the data sets more pronounced.

4. Conclusions

We quantified green and blue water consumption, including partitioning blue water into surface water and groundwater, for major irrigated crops in the CONUS each month from 1981 to 2019 at the spatial resolution of 2.5 arc min. Our findings indicate that the average blue VCWC of irrigated crop production in the CONUS is approximately 108 km^3/year. This figure is nearly equivalent to the maximum storage capacity of the three largest man-made reservoirs in the US. Additionally, our study reveals distinct regional trends in VCWC within the CONUS: there is generally a decreasing trend in the western states and an increasing trend in the eastern states. Our publicly available models and MIrAg-US enable researchers and policymakers to assess historical crop water consumption, as well as investigate hypothetical scenarios and testing of different strategies to identify optimal irrigation practices without relying solely on lengthy and expensive field experiments. Researchers and water managers can integrate the CWC estimates from this study with economic data, such as crop costs and profits, to identify opportunities for crop switching that reduce water consumption while maintaining economic value.

The data set, MIrAg-US, provides estimates of CWC that can be used to aid in water budgets, hydrologic assessments, benchmarking that is, obtaining initial estimate of how much water is required to grow a crop in a particular area, and regional crop water demand estimates, among other purposes. However, it should not be used for regulating water use or assessing the irrigation use of a specific individual since local conditions, including water availability, farm management, technology, and other circumstances, may lead to irrigation applications that differ from our modeled values. Notably, farm management and irrigation practices vary widely across farmers and these diverse behaviors could not be fully accounted for in our model due to limitations of the model and data availability. Therefore, we reiterate that MIrAg-US represents the amount of water required to grow a given crop under the specified conditions and assumptions of this study, not necessarily the amount of water a specific farmer used within a given month.

The magnitude of crop water consumption (CWC) for a state or specific grid has significant implications for water resource management, agricultural productivity, and sustainability. Regions with higher CWC indicate elevated irrigation demands, which can strain local water supplies and contribute to environmental degradation. Since water consumption often serves as a proxy for crop production, areas with high water use typically correspond to regions of substantial agricultural output. Notably, a small percentage of land in the U.S. accounts for the majority of water consumption and, by extension, food production. Any disruption to water supplies in these critical regions—whether due to severe drought, infrastructure failure, or water reallocation—could have profound consequences for food security.

While our data set provides valuable insights, several uncertainties are associated with the results due to limitations in the models, input data sets, or both. Our estimates of CWC are derived from two models: AquaCrop-OS and a simple crop growth model—each with varying levels of accuracy and uncertainty. Additionally, uncertainties in input data sets, including climate data, irrigated harvested area, crop parameters, and irrigation management parameters, are reflected in our results. We also made several assumptions during the analysis, such as assuming a uniform surface water fraction across all grids within a county for all crops. Furthermore, due to data unavailability, we used surface water fraction values from other years to fill gaps, which may introduce additional uncertainty when partitioning blue CWC into surface water CWC and groundwater CWC. The crop models used in this study have several limitations, including the inability to capture observed farm management practices, such as actual irrigation frequency and duration. Instead, our model employs a simplistic representation of irrigation application, assuming optimal scheduling and uniform practices, which may not align with real-world variability. The model also does not account for the impacts of pests, diseases, or variations in fertilizer application, which can also influence crop growth and water use.

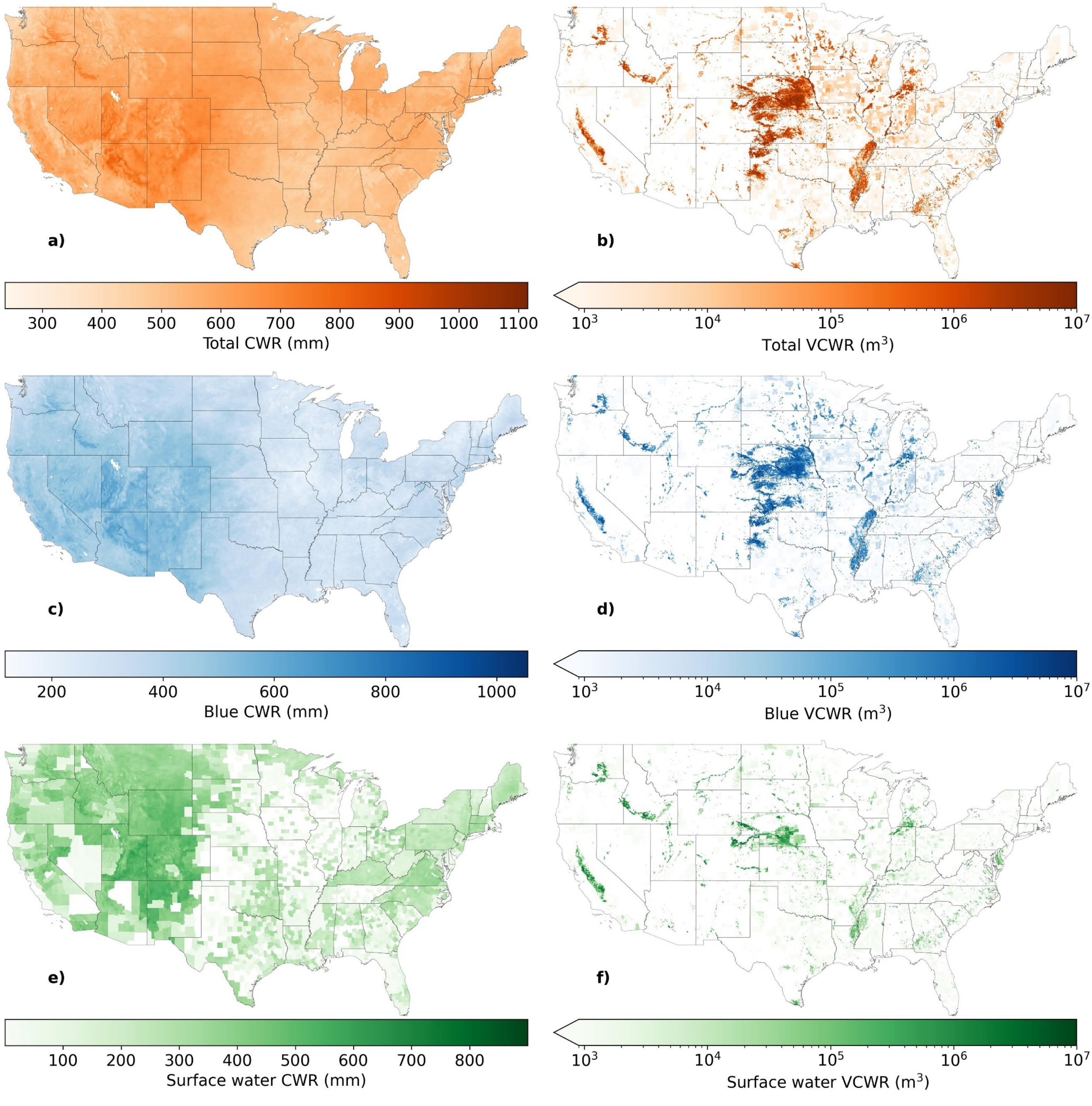

Figure 9. Maps illustrating (a) total CWC (mm), (b) total VCWC (m^3), (c) blue CWC (mm), (d) blue VCWC (m^3), (e) surface water CWC (mm), and (f) surface water VCWC (m^3) for corn within each 2.5 arc-minute grid cell. Data shown here are for the year 2010.

To demonstrate the advancements made by our study and to transparently show the degree modeling choices and input data shape CWC estimates, we compared our model estimates against some of the most widely cited CWC data products. First, we compared total CWC depth with modeled estimates from previous global CWC models and OpenET. Second, we then compared blue CWC depth with records from USDA and volumetric blue CWC with records from USGS. We find that our crop estimates are generally in agreement with other data sources; however, the degree of agreement varies depending on crop type, models being compared, and geographical region. These differences highlight the complexities and uncertainties associated with estimating CWC and emphasize the need for further research and refinement in this area, particularly as it relates to validation data.

Table 2
Overview of the Data Products

Variable	Description
Total CWC	The depth of water (mm) required to support crop growth in each 2.5 arc min grid cell by month from 1981 to 2019 for the CONUS.
Total VCWC	The volume of water (m^3) required to support crop growth in each 2.5 arc min grid cell by month from 1981 to 2019 for the CONUS.
Blue water fraction	The fraction of blue water required to fulfill the total CWC. The remaining total CWC comes from green water.
Surface water fraction	The fraction of the blue water consumption fulfilled by surface water. The remaining blue water consumption comes from groundwater.

Note. All data can be retrieved from the data repository HydroShare (Lamsal & Marston, 2024c). It can also be retrieved through the following link https://www.hydroshare.org/resource/8134f362b45147d8aebf02b71253213e/.

Future research should explore opportunities for combining estimates from process-based models, like the one used in this study, with remotely sensed data. Actual ET estimated from satellites can constrain ET estimates from process-based models, while the process-based model can partition remotely sensed estimates into irrigation components (i.e., blue CWC) and the precipitation component (i.e., green CWC).

We demonstrate that the crop growth models are effective tools for estimating CWC, utilizing detailed and unique data sets available for the US to produce high-resolution spatial and temporal CWC estimates. The modeling framework developed in this research can be applied to other geographical regions or different time periods to produce similar estimates. Additionally, the detailed data set produced from this research provides valuable insights into spatial and temporal variations in crop water consumption across the US, offering critical information that can aid policymakers and water managers in promoting sustainable water management practices.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

This research provides four data sets: (a) total CWC, (b) total VCWC, (c) blue water fraction, and (d) fraction of blue water from surface water, which are publicly available through the data repository Hydroshare (Lamsal & Marston, 2024c). The information on each crop is provided using a NetCDF4 file. Each NetCDF4 crop file has two spatial coordinates (lat, lon), two temporal coordinates (month, year), and four variables (Total CWC, Total VCWC, blue water fraction, and surface water fraction). Total CWC (Figure 9a) and total VCWC (Figure 9b) can be partitioned into blue and green components when multiplied by the corresponding blue water fraction; this yields the blue CWC (Figure 9c) and the blue VCWC (Figure 9d). Subtracting the blue component from the total CWC (or VCWC) yields the green component. Similarly, blue CWC or blue VCWC can be partitioned into surface water and groundwater when multiplied by the corresponding surface water fraction; this yields the surface water CWC (Figure 9e) and surface water VCWC (Figure 9f). Subtracting the surface water component from the blue component yields the groundwater component. An overview of the data products and description of each data product is available in Table 2.

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