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A High Spatiotemporal Assessment of Consumptive Water Use and Water Scarcity in the Conterminous United States

Brandon C. Moore[1,2] · André M. Coleman[1,3] · Mark S. Wigmosta[1] · Richard L. Skaggs[1] · Erik R. Venteris[1,4]

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Abstract There is an inextricable link between energy production and food/feed/fiber cultivation with available water resources. Currently in the United States, agriculture represents the largest sector of consumptive water use making up 80.7 % of the total. Electricity generation in the U.S. is projected to increase by 24 % in the next two decades and globally, the production of liquid transportation fuels are forecasted to triple over the next 25-years, having significant impacts on the import/export market and global economies. The tension between local water supply and demand across water use sectors needs to be evaluated with regards to risk evaluation and planning. To this end, we present a systematic method to spatially and temporally disaggregate nationally available 5-year county-scale water use data to a monthly 1/8° scale. Our study suggests that while 81.9 % of the U.S. exhibits unstressed local conditions at the annual scale, 13.7 % is considered water scarce; this value increases to 17.3 % in the summer months. The use of mean annual water scarcity at a coarser basin scale (~373,000 ha) was found to mask information critical for water planning whereas finer spatiotemporal scales revealed local areas that are water stressed or water scarce. Nationally, ~1 % of these "unstressed" basins actually contained water stressed or water scarce areas equivalent to at least 30 % and 17 %, respectively, of the basin area. These

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✉ André M. Coleman
Andre.Coleman@pnnl.gov

1 Pacific Northwest National Laboratory, Hydrology Technical Group, MSIN K9-33, P.O. Box 999, Richland, WA 99352, USA

2 Department of Geography, University of Idaho, McClure Hall 203, P.O. Box 443021, Moscow, ID 83844-3021, USA

3 Glenn Department of Civil Engineering, Clemson University, Lowry Hall, Clemson, SC 29634-0911, USA

4 Present address: Monsanto Company, 800 North Lindbergh Blvd., St. Louis, Missouri 63167, USA

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percentages increase to 34 % and 48 % in the summer months. Additionally, 15 % of basins classified as "unstressed" contained water scarce areas in excess of 10 % during the summer.

Keywords Water demand · Water supply · Energy security · Water-energy nexus · Sustainability · Agriculture · Bioenergy

1 Introduction

Increasing demands for energy production and national objectives for securing energy independence from foreign sources of energy, both renewable and non-renewable, are heavily dependent on available water resources. The explicit interdependency between energy production and required water resources is commonly referred to as the "water-energy nexus" (DOE 2006, 2014; McMahon and Price 2011; GAO 2012). This entails the use of water from surface and groundwater resources to address needs across the energy spectrum including extractions and processing of traditional fossil-fuel sources (e.g., crude and shale oil, natural gas, and coal), mining and processing of nuclear fuels, power-generation, and agriculture supporting bioenergy feedstocks. Agriculture represents the largest sector of consumptive water use in the conterminous United States (CONUS), with irrigated agriculture making up 80.7 % of the total consumptive use, followed by domestic (7.3 %), industrial (4.2 %), thermoelectric (3.9 %) livestock (3.1 %), and mining (0.8 %) sectors (U.S. Geological Survey 2010). The energy sector is growing rapidly, requiring additional water resources. For example, global production of liquid transportation fuels sourced from biomass, coal, and natural gas are forecasted to triple by the year 2040 (EIA 2013). Electricity generation in the U.S. is projected to increase by 24 % in the next two decades and thermoelectric consumptive water could increase dramatically beyond just increased power demand, but also due to technology changes such as closed-loop cooling systems (Tidwell et al. 2012); however, the Electric Power Research Institute cautions that water availability makes thermoelectric power production vulnerable (EPRI 2011). The production of liquid transportation fuels are forecasted to triple over the next 25-years with a projection that 27 % of these fuels will be sourced from renewable biomass (IEA 2011). Not only do the agriculture and energy sectors have increasing demands, but other sectors such as industry and municipal supply have growing requirements for water as well.

Increasing water demands in the U.S. can, in part, be explained by a growing national population. The period from 2000 to 2010 saw a 9.7 % (27.3 million) increase in population with 52 % of that growth occurring in the southern U.S. followed by 31 % in the western U.S. (U.S. Census Bureau 2010). In addition, geographically shifting populations impact local resources, where 11 U.S. states have seen >15 % increases in growth, and 5 of those states experienced >20 % growth over the same time period. There is a subsequent and inter-related increased demand for energy, water, land, and associated societal services and these increased water demands are compounded by a higher frequency of variability in inter-annual climate, more frequent extreme climatological events, and long-term altered climates, all of which impact the quantity, timing, and geography of available water resources (Skaggs et al. 2012).

The competition for available water resources is also understood by evaluating the quantity, timing and spatial distribution of water availability and use. The location and timing at which water is available and consumed dominantly affects the extent to which not only energy and water influence one another, but also the greater crosssector dependencies that for example, influence agriculture, industry, environment, economics, and social well-being (Skaggs et al. 2012). The understanding of available water resources and its use at a high spatiotemporal resolution is critical for shaping future water use policy and management, planning for change-based impacts at the local level, and resolving prevalent issues and priorities now and into the future (U.S. Water News Online 2002; Curlee and Sale 2003; GAO 2012; DOE 2014).

To this end, we present a new CONUS-wide systematic spatial and temporal disaggregation method that overcomes commonly-used spatiotemporal scales by extracting and utilizing key information from numerous datasets including 1) nationally-available, 5-year averaged, county-scale, sector-specific water use data; 2) remotely-sensed land use/land cover data; 3) U.S. Census population data; 4) point-based geographic features; and 5) spatially distributed meteorological time-series data, to produce monthly sector-specific consumptive water use and water scarcity data at a scale suitable for use in local basin planning. The utility of this approach is demonstrated by evaluating water scarcity across multiple temporal and spatial scales and assessing the potential risk to current agricultural crops/croplands and viability of future bioenergy crops.

2 Scale

The majority of water use studies are conducted at the watershed, county or state/province level (Solley 1997; Ramireddygari et al. 2000; Franczyk and Chang 2009; Tidwell et al. 2012; Chiu and Wu 2012; Averyt et al. 2013) but seldom at the local scale (Roy et al. 2005). While consumptive water use at coarser spatiotemporal scales provides important information regarding the overall impact of water availability, it fails to address the needs of local scale decision making (Doll and Siebert 2002; Gain and Wada 2014). Roy et al. (2005) developed a methodology to temporally disaggregate annual water use data to a monthly time-step using precipitation and potential evapotranspiration (PET). These data exist nationally at the county scale; however the area representation of a county is highly variable across the country and is not always applicable for local scale analysis. The potential then exists to discount the spatial variability and subsequent impact of available water resources and scarcity arising from changes in climate, land use, and population at the local level (Karl et al. 2009).

3 Methodology

3.1 Consumptive Water Use

To help define trends and plan for future water requirements, the USGS compiles data from various sources that represent average water use for the previous 5 years and produces county-scale, sector-specific water use data (Hutson et al. 2004; Solley et al. 1988, 1993; Solley 1997). In this study, four datasets (1985, 1990, 1995, 2000) spanning 20 years were used to spatially and temporally disaggregate consumptive water use in the irrigation/agriculture, domestic, industrial, thermoelectric, livestock and mining sectors (U.S. Geological Survey 2010).

3.2 Spatial Disaggregation

Each consumptive water use sector is spatially disaggregated from the native county scale to a 1/8° resolution (i.e., for the CONUS, approximately 144 km^2), matching the horizontal resolution of many hydrologic models and associated datasets (Liang et al. 1994; Maurer et al. 2002; Mitchell et al. 2004). The type of water use is associated with either a particular land use/land cover type (e.g., cropland, urban) or geographic feature (e.g., thermoelectric locations, census blocks). Consumptive water use sectors are broken down separately into three groups: domestic, thermoelectric, and other. The initial step to disaggregate all water use sectors requires intersecting a U.S. county boundary layer with a 1/8° model grid. Ratios between the county grid and local scale features are developed for each water use sector and applied to the county-wide consumptive water use.

3.2.1 Domestic

Domestic water use is assumed to be proportional to population. The spatial disaggregation of domestic consumptive water use requires a spatially distributed population dataset to develop the appropriate weights for population distribution to each 1/8° grid cell. For this study, data from the U.S. 2000 Census (U.S. Census Bureau 2000) assumes a uniform population distribution throughout a given census block. The 2000 data was utilized in place of more current 2010 data to better represent the time-period being evaluated. We spatially disaggregate domestic consumptive water use by intersecting the census block data with the 1/8° county grid, after which the total area for each census block that falls within a 1/8° grid cell is calculated. The intersected census block cell area is divided by the total area of the original census block to determine an area-weighted ratio of the intersected census block for each 1/8° grid cell. The area-weighted ratio is then multiplied by the census block population to determine the block population of each intersected area. Since census blocks do not overlap county political boundaries, the block population of each intersected area is divided by the county population to produce the final spatial disaggregation weights.

3.2.2 Thermoelectric

Textual locations of thermoelectric facilities obtained from the U.S. Department of Energy's Energy Information Administration (EIA 2010) were geocoded into a point-based spatial dataset. Consumptive water use coefficients vary among facility types (Fthenakis and Kim 2010); however since this information wasn't available at the time of the study, all thermoelectric plants were treated equally in terms of consumptive water use. Thermoelectric consumptive water use is spatially disaggregated by summing the number of thermoelectric facilities located within each intersected 1/8° county grid cell. The ratio of the number of thermoelectric facilities in each intersected 1/8° cell to the total number of facilities within a given county provides the final spatial disaggregation weight.

3.2.3 Industrial, Irrigation, Livestock, and Mining

Remotely-sensed land use/land cover data from the Gap Analysis Program (GAP; U.S. Geological Survey 2009; Gergely and McKerrow 2013) was used to spatially disaggregate the remaining USGS consumptive water use sectors: irrigation, industrial, mining and livestock. The

GAP dataset provides a classification system that represents all required land use types to match the consumptive water use sectors. To generate the spatial weights, a ratio for each of the aforementioned classed land areas to the total area within each 1/8° county grid cell is determined. The final spatial weights are the product of each classed land-area ratio and the ratio of the 1/8° county grid cell area to the total county area.

3.2.4 Total Consumptive Water Use

The final spatial disaggregation steps apply the weights to the consumptive water use at the county scale and water use sums for each sector within each 1/8° grid cell (Fig. 1a). The spatial disaggregation ratios for each 1/8° county grid cell are multiplied by the corresponding county-scale consumptive water use categories. The cells that comprise each 1/8° area are summed to provide a total consumptive water use (Fig. 1b).

3.3 Temporal Disaggregation

While generalizations can be inferred using annual consumptive water use data, the lack of intra-annual information hinders finer-scale use patterns. For example, if the annual consumptive water use for irrigation in Florida is evenly divided across each month, a seasonal bias would exist due to changes in precipitation patterns throughout the year (Marella 2008). To overcome this limitation, the spatially disaggregated 5-year annual average consumptive water use data are temporally partitioned utilizing different schemes depending on the water use sector. For the industrial and mining sectors, consumptive water use is weighted evenly across the year as these operations are typically not seasonally varying. A temperature-centric weighting scheme based on the apparent temperature departure from sector-specific thresholds is utilized for thermoelectric, domestic and livestock. To generate temporally-disaggregated irrigation water use, monthly precipitation and PET are used. The annual spatially disaggregated sectors are multiplied by the corresponding monthly ratios (weights) to produce spatio-temporally disaggregated grids of consumptive water use.

3.3.1 Temperature Based Weighting

Since air temperature alone doesn't always represent realistic conditions for electricity demand and heat stress (i.e., hot and humid or cold and dry days) (Gupta 2012; Kalkstein and Davis 1989), apparent temperature is incorporated in the weighting scheme. The apparent temperature (*AT*) calculations use spatially distributed meteorological variables including temperature, wind (Maurer et al. 2002), and humidity (Livneh et al. 2013) as follows (Steadman 1994):

$$AT = T_a + 0.33e - 0.70ws - 4.00 \tag{1}$$

where T_a is air temperature (Celsius), e is water vapor pressure (hPa) (Sun et al. 2002), and ws is wind speed (m/s).

Degree days, both heating and cooling, were used to partition the annual consumptive water use sectors for thermoelectric, domestic and livestock to a monthly value. A heating/cooling degree day is a measure of how many degrees the outside air is above/below a threshold temperature (Bonhomme 2000). For thermoelectric water use, it is assumed that water use will be greater when the demand for energy is higher for heating or cooling based on a temperature

Fig. 1 Percent of annual consumptive use relative to the total consumptive water use for each water use sector averaged over 1981–2000 (**a**), and the total annual consumptive use in million gallons per day (mgd) (**b**). *Black areas* indicate locations where there is no consumptive water use

threshold of 18 °C (European Commission 2010). This threshold allows for the use of the monthly ratio of total degree days, regardless of it being a cooling or heating degree day. Temporal partitioning of domestic and livestock water use are dependent on only cooling degree days. It is assumed that domestic consumptive water use is higher during the summer when additional water is utilized for yard watering and other household uses (U.S. Geological Survey 1997; Shaffer 2009). Monthly partitioning of water for livestock is also based on the departure of temperature above a base temperature of 18 °C to allow for increased water for facility and/or animal cleaning and increased drinking water requirements (Shaffer 2009; Lardy et al. 2008).

To determine the monthly temporal weights for the thermoelectric, domestic, and livestock sectors, first, the consumptive water use is evenly divided so each month accounted for 1/12th of the annual total. Next, the heating/cooling degree days are determined when the apparent temperature departed from 18 °C. The total degree days for each month are then divided by the annual sum of degree days. For months when the degree day ratio is greater than zero, the water use is increased accordingly and the water use of the remaining months is uniformly decreased to maintain water accounting.

3.3.2 Irrigation Weighting

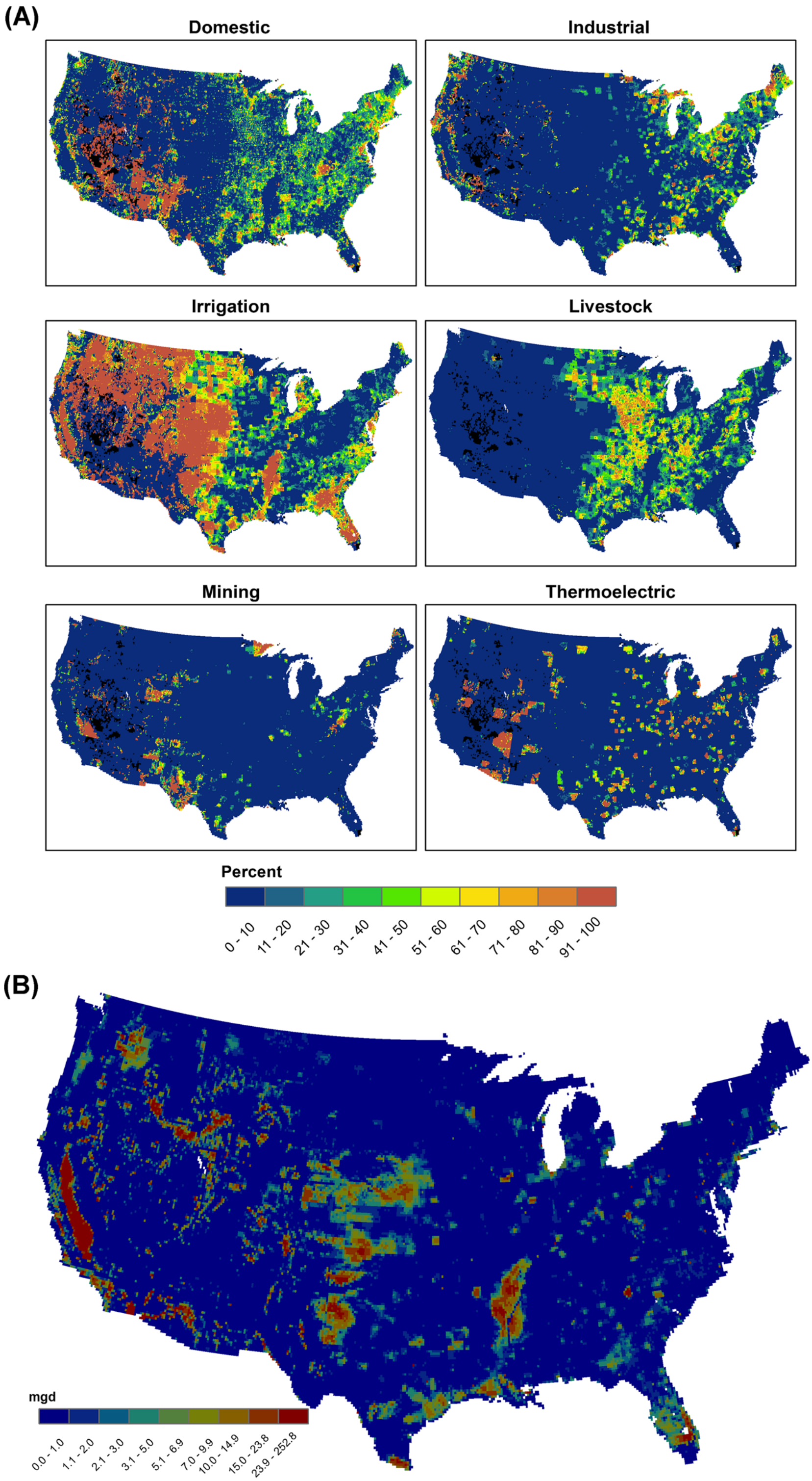
Multiple methods were examined to determine the optimal approach to estimate monthly consumptive water use for irrigation (Table S1). The degree day method computes a ratio of the monthly cooling degree days to the total cooling degree days of a given year. This method generally produces a normal distribution of monthly weights centered over the summer season; however, it does not account for any water deficit caused by the seasonal fluctuation of precipitation. Another method, the inverse aridity index (Bannayan et al. 2010), utilizes the ratio of precipitation and PET to assign monthly weights. This method may potentially weight 2 months equally although the monthly water deficits (precipitation – PET) may be dramatically different (e.g., 2 months have the same ratio but water deficits are 1-cm and 10-cm respectively). A third method, the water deficit proportion (Roy et al. 2005), determines irrigation weights using the proportion of the monthly difference between precipitation and PET. This method places more emphasis on months where the water deficit is greater.

The first step in the water deficit proportion method computes an initial value (x_i) based on water deficit:

$$x_i = \left| \frac{1}{prcp_i - PET_{Hi}} \right| \quad when \;\; prcp \; > PET_H \tag{2}$$

$$x_i = |prcp_i - PET_{Hi}| \quad when \;\; prcp \leq PET_H \tag{3}$$

where $prcp$ and PET_H (Hamon 1963) are precipitation and PET, respectively, for a given month (i). Equations (2) and (3) are a necessary step given that an area may irrigate even though precipitation exceeds PET. While more physically-based approaches are available, data availability limited the scope of this work to an empirical approach. The monthly weight is the


(A)
Domestic
Industrial
Irrigation
Livestock
Mining
Thermoelectric
Percent
0 - 10
11 - 20
21 - 30
31 - 40
41 - 50
51 - 60
61 - 70
71 - 80
81 - 90
91 - 100
(B)
mgd
0.0 - 1.0
1.1 - 2.0
2.1 - 3.0
3.1 - 5.0
5.1 - 6.9
7.0 - 9.9
10.0 - 14.9
15.0 - 23.8
23.9 - 252.8

proportion of each monthly value (x_i) to the sum of all monthly values within a given year. Although this method accounts for water deficit months, the possibility exists for weights to be assigned during the cooler months when irrigation should not occur.

To further constrain the water deficit proportion method, we investigated both the growing season length (Brinkmann 1979) and a growing season index (Jolly et al. 2005) to determine when irrigation begins and concludes. The growing season length method assumes that irrigation begins with the first occurrence of five consecutive days ≥ 5 °C in the spring and finishes in the fall when temperatures reach < 5 °C for five consecutive days. Monthly irrigation weights using Eqs. (2) and (3) are only calculated for months between these two time periods. Months that contain the start and end dates are weighted by the fraction of growing season days to total days in the month. While including growing season length in the water deficit proportion method helps remove some irrigation during the cooler months, late winter warm-ups and/or short duration temperature drops in the early fall can have a pronounced effect on irrigation timing. To address this, we used the growing season index, which is a phenological approach based on the combination of daily minimum temperature, vapor pressure deficit, and photo period (Jolly et al. 2005). Meteorological variables are converted to daily indicators that represent plant sensitivity to low temperatures, water stress, and solar radiation duration respectively. In turn, the daily indicators are combined to create a daily growing season indicator (*iGSI*):

$$iGSI = iT_{\min} * iVPD * iPhoto \tag{4}$$

where $iT_{\min}$ is the daily minimum air temperature indicator, $iVPD$ is the daily vapor pressure deficit indicator, and $iPhoto$ is the daily photo period indicator. The growing season index is generated as the product of the daily indicators smoothed over a 21-day moving window, thus removing undue influences of extreme meteorological events that may prematurely trigger the start or end of the growing season. Final irrigation weights are computed in a similar manner as the growing season length method where months that contain the start and end dates are weighted by the fraction of growing season days to total days in the month.

4 Results and Discussion

4.1 Spatially Disaggregated Consumptive Water Use

While generalizations of consumptive water use can be obtained using county-level data, the data presented here allows for more detailed analysis at the local scale. We have observed that significant amounts of annual consumptive water use can be concentrated in areas smaller than the county scale (e.g., thermoelectric). Examining the contributions of each consumptive water use sector provides additional insight regarding the spatial distribution of annual water use (Fig. 1). Domestic and industrial consumptive water use dominate all water use sectors in the population centers of the eastern U.S., Midwest, and the Pacific Coast. What is notable and possibly misleading are the large areas of land in the southwestern U.S. (i.e., Nevada, Arizona, New Mexico) where domestic consumptive use is dominant. This is not the result of large metropolitan areas, but rather these regions are sparsely populated and the limited available water is dominantly used for domestic purposes. Livestock consumptive water use dominates the rural portions of the Midwest and eastern U.S. with the existence of concentrated animal feeding operations and is less dominant in the western U.S. as livestock grazing on pasture and rangeland is common.

While mining and thermoelectric water use are scattered throughout the CONUS and account for relatively large percentages of localized consumptive water use, they only account for approximately 4 % of the overall national consumptive water use. Irrigation, comprising almost 81 % of all consumptive water use, is dominant throughout many areas in the U.S.

4.2 Spatially Disaggregated Seasonal Consumptive Water Use

As might be expected, the pattern of consumptive water use generally increases as temperatures warm in the spring and decreases again in the fall (Fig. 2). This pattern generally highlights locations that are high in irrigation-based consumptive water use and follows the natural progression of the agricultural growing season. However, it should be noted that areas such as south-central Florida exhibit an increase in consumptive water use from the fall through the spring and minimal use is seen during the warmer summer season (Fig. 3). This is the result of the dominant Florida crops being grown and harvested in non-summer months along with an increase in summer precipitation, thus a reduced requirement for irrigation (Marella 2008). Unique seasonal water scarcity areas such as this demonstrate the utility of the temporal disaggregation scheme.

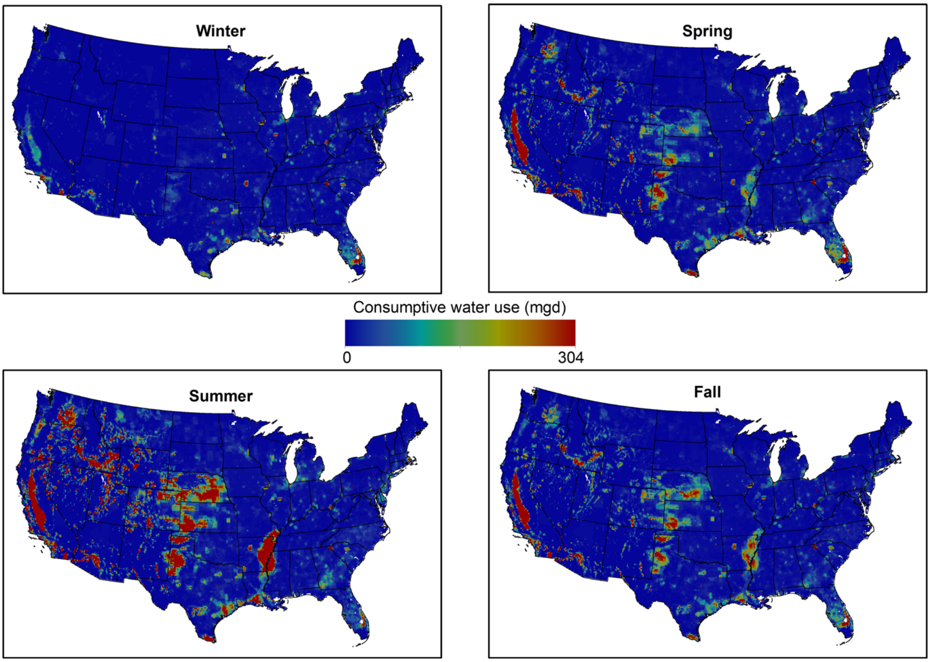


Fig. 2 Seasonal estimates of consumptive water use for Winter (DJF), Spring (MAM), Summer (JJA), and Fall (SON) at the local level

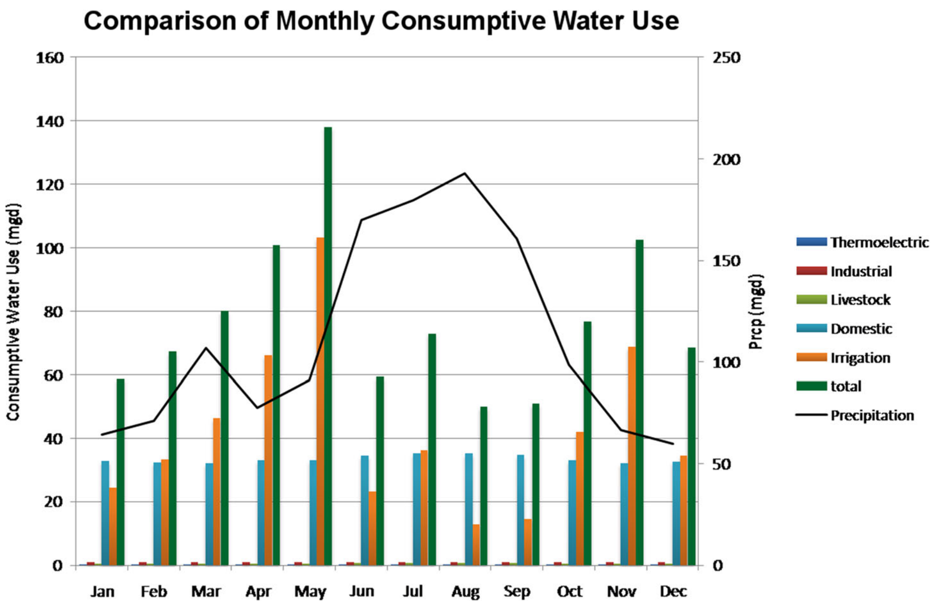


Fig. 3 Monthly disaggregated consumptive water use (*bars*) and monthly precipitation (*line*) at a single 1/8° cell in south-central Florida for all consumptive water use variables

5 Analysis of Disaggregated Water Use and Impact on Water Scarcity

Spatially and temporally disaggregated consumptive water use data are critical for investigating unsustainable use of water resources, the allocation and timing of available water, and determining localized water stress. Certain regions of the U.S. are experiencing changing hydroclimatic patterns with seasonal shifting and/or changes in the quantity and type of precipitation (Sagarika et al. 2014). Thereby for some areas, water supply may not meet the timing for when irrigation is needed, and consequently increasing water scarcity and competition for available water. We examine water scarcity over a range of spatial and temporal scales along with the potential impact on agriculture.

Water scarcity for each 1/8° grid cell is computed to provide a broad view of competition for available water. If consumptive water use at a specific location is high relative to the local runoff, then competition increases and water becomes scarcer. Numerous methods exist to compute water scarcity (Brown and Matlock 2011). In this study water scarcity is defined as:

$$water\_scarcity = \frac{consumptive\_water\_use}{runoff} \tag{5}$$

where runoff is the upstream accumulated runoff for each 1/8° grid cell within a given 8-digit USGS hydrologic unit code (HUC) basin. There are 2106 8-digit HUCs within the CONUS ranging from 9623 to 2,278,070 ha with a mean area of 373,335 ha. Local estimates of average monthly runoff from 1980 to 2000 at the 1/8° resolution were computed using USGS 8-digit HUC runoff data (Brakebill et al. 2011), 1/8° monthly total precipitation and Hamon (1963) PET. The precipitation and PET data provides spatial and temporal meteorological information within each HUC, while the runoff data supplies the timing and magnitude of the runoff. The difference between the monthly precipitation and PET is determined for each 1/8° cell. If the difference is negative, a value of zero is assigned. The difference value for each cell is then divided by the total cell differences within a HUC to produce a local monthly weight for each cell. Local runoff is the product of the monthly runoff for the HUC and the local weight.

5.1 Annual Water Scarcity

Water scarcity is categorized as unstressed (<0.2), stressed (>=0.2 and <0.4) and scarce (>=0.4) (Sun et al. 2008). A dichotomy exists between the water abundant eastern U.S. and the highly irrigated Midwest and west (Fig. 4). While 81.9 % of the CONUS exhibits

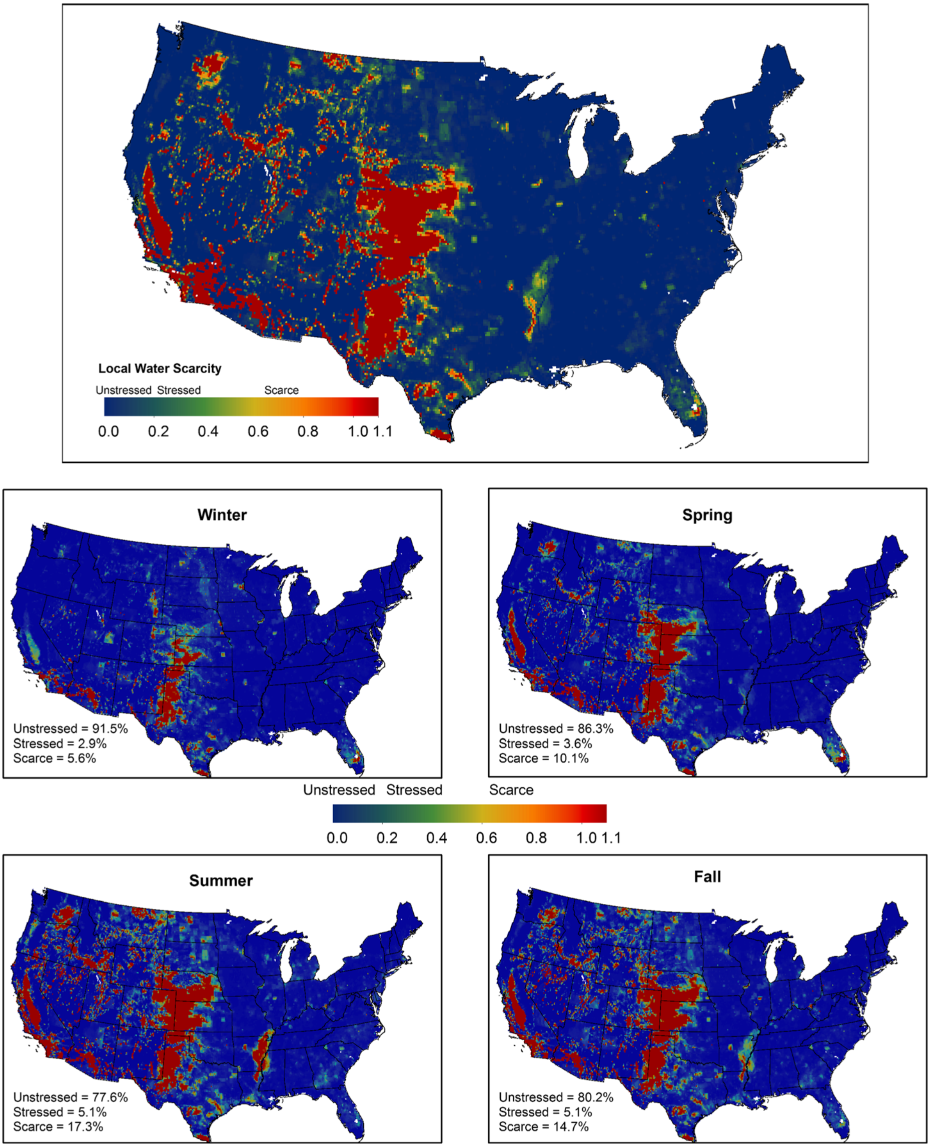


Fig. 4 Annual and seasonal (Winter=DJF; Spring=MAM; Summer=JJA; Fall=SON) water scarcity at the local level throughout the CONUS

unstressed conditions, 13.7 % is considered water scarce. The highly cultivated area in the vicinity of the Ogallala Aquifer is the largest contiguous area of local water stress in the U.S. Limited precipitation pushes this area to a highly water stressed classification; however, agriculture has subsisted in this region as a result of ground water mining over the past 65-years. The eastern portion of the U.S. is generally unstressed for water except areas such as the Mississippi River Plain and south-central Florida. These areas have relatively high amounts of irrigation water use in a region typically dominated by domestic and livestock consumptive water use.

5.2 Seasonal Water Scarcity

Generally, regions of annual water scarcity are persistent throughout the year (Fig. 4), and the levels of water stress and the scarcity percent area changes by season. Portions of the Ogallala Aquifer region remain water scarce throughout the year; however, areas such as the Walla Walla Plateau in eastern Washington, California's Central Valley, and the Mississippi River Plain all begin relatively unstressed in the winter and become more stressed as irrigation increases and precipitation patterns change throughout the year. South-central Florida also exhibits water scarce conditions throughout the year except during the summer, which coincides with the region's rainy season (Fig. 3).

5.3 Influence of Scale on Assessment of Water Scarcity

The spatial and temporal scales at which water scarcity is assessed have a pronounced effect on the perceived severity (Figure S2). Analysis at the 2-digit HUC (mean annual) scale shows approximately 56 % of the CONUS is unstressed and the remainder is stressed, with no areas identified as water scarce. However, analysis at the 4-digit HUC (mean annual) scale indicates 11.1 % of the CONUS is water scarce and this value increases to 13.7 % at the 1/8° scale and 17.3 % for the summer months. The central plains and portions of the southwestern United States have increased areas of water scarcity as the spatial resolution becomes finer, often highlighting regions that are highly water stressed, generally as a result of irrigation. The water scarcity differences between the 6-, 8-digit HUCs and 1/8° emphasize the need for careful scale consideration when assessing water scarcity estimates in support of developing and executing local water policy (Fulton et al. 2014).

The 8-digit HUCs classified as unstressed at the annual scale may contain a significant percent of local areas that are water stressed or water scarce (Table 1). Approximately 1 % of these "unstressed" HUCs contains water stressed or water scarce areas equivalent to at least 30 % and 17 % of the HUC area, respectively. These values increase to 34 % and 48 %, respectively, in the summer months. Approximately 15 % of these "unstressed" HUCs contain water scarce areas in excess of 10 % during the summer months. To demonstrate, an 8-digit HUC (18050002), located north of San Francisco, California consists of irrigated crops in the north, and primarily domestic and industrial water use in the south. This HUC is classified as unstressed at the mean annual scale and remains so through the spring. However, in the summer months, almost 88 % of the land area is classified as water scarce at the 1/8° scale (Fig. 5). This is primarily due to increased irrigation to replace minimal precipitation during the summer growing season.

Table 1 Percent of 1/8° cells classified as stressed or scarce within 8-digit HUCs classified as unstressed at the annual and Summer (JJA) time scale

% 8-digit HUCs	Percent of 1/8° cells equal or greater than			
	Annual time scale		Summer only	
	Stressed	Scarce	Stressed	Scarce
1	30.0	17.0	33.9	48.1
5	13.8	11.3	20.0	23.4
10	8.5	6.8	13.6	13.4
15	5.6	3.5	9.9	10.2
20	3.7	0.9	7.1	6.4
25	1.6	0.0	5.1	3.8
30	0.3	0.0	3.4	1.4

6 Water Scarcity by Crop

The large water demand in the agricultural water use sector requires a more in-depth look at a variety of agricultural crops currently grown in areas of varying water scarcity. Local water scarcity is combined with the most commonly occurring crop type at the 1/8° scale and provides a unique perspective on sustainability. While individual crop irrigation rates were not taken into account in the consumptive water use disaggregation scheme, it can be informative of the overall pattern for the CONUS. Figure 6 provides the percent of land area for annual water scarcity based on a variety of common crops. From the analysis at the annual scale, sorghum, barley, cotton, rice, and food crops have >40 % of their cultivated lands in a 'scarce' water state, whereas tobacco, peanuts, pasture/forage, other biofuels, and corn/soy beans exceed 80 % of their cultivated land in an 'unstressed' water state; however this can change annually depending on meteorological patterns.

As aquifer levels continue to decrease from mined groundwater, the sustainability of crops grown in water scarce regions also decreases. Analyzing the impact crops have on local water supplies and the resulting water scarcity provides a method for determining where and when

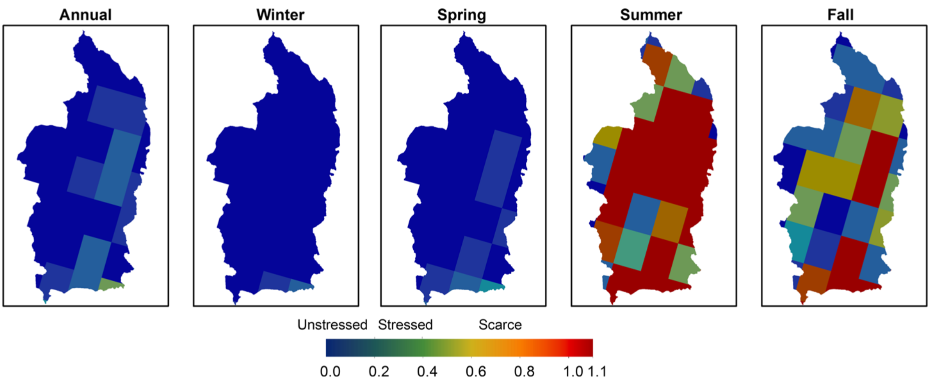


Fig. 5 Increased temporal resolution at 1/8° resolution, even at the seasonal scale, reveals important water scarcity patterns not witnessed in the mean annual data

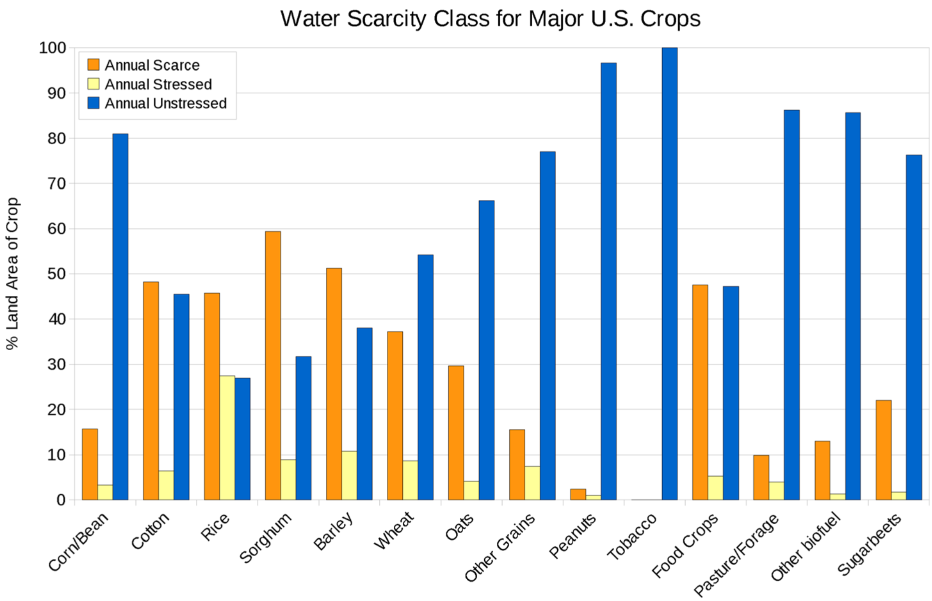


Fig. 6 The percent land area categorized into one of three water scarcity classes for 14 major crops types in the CONUS

the water-energy nexus and agricultural sustainability becomes more challenging. Proactive agricultural adaptation and mitigation strategies will be required to increase the resilience and sustainability of agriculture. For example, replacing water intensive crops (i.e., cotton, corn, rice) in water scarce regions with more water efficient crops, including bioenergy crops such as camelina, canola, safflower, switchgrass, and/or miscanthus, can provide direct water savings as well as secondary benefits including improved soil physical and chemical characteristics that can increase soil moisture capacity.

7 Summary and Conclusions

In this paper we provide a methodology to spatially disaggregate county-scale consumptive water use data by water use sector to a 1/8° spatial resolution providing a consistent and locally relevant spatial unit for which models, analysis, and planning can be based upon. Further, we presented a method to temporally partition 5-year average spatially disaggregated consumptive water use to monthly estimates in order to understand seasonal water use impacts amongst the different water use sectors. The spatially and temporally disaggregated water use data was then used to examine water scarcity by several means including seasonal and spatial patterns, the influence of spatial scale on water scarcity information, and potential risk to crops due to conditions of limited water availability. Our results demonstrate that valuable information may be obtained regarding the competition of water and the resulting water scarcity at the local level. Various means of risk evaluation, planning, policy development, and adaptation to changes in hydroclimate and consumptive use patterns with regards to the water-energy nexus and sustainability and adaptability of energy production, agriculture, environment, and socioeconomics can and should be informed by incorporating high-resolution spatiotemporal estimates of local water scarcity.

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