REGIONAL SCALE CHARACTERIZATION AND ASSESSMENT OF WATER USE AND COMPETITION IMPACTS FOR U.S. FOOD CROPS

by

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A thesis submitted
in partial fulfillment of the requirements
for the degree of
Master of Science
(Natural Resources and Environment)
at the University of Michigan
April 2017

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Acknowledgements

This thesis was greatly supported by the work of Dr. Anne-Marie Boulay and Dr. Stephen Pfister, both of which generously and graciously provided data from their current research efforts to act as key inputs into the methodology used in my work. Dr. Anne-Marie Boulay provided basin-level water characterization factors, and Dr. Stephen Pfister provided basin-level irrigation water values for over 160 different crops. Without the support and data sharing from these to researchers, this thesis would not have been possible.

Dr. Greg Keoleian acted as the primary advisor on this thesis and, without his insight and mentoring, the depth and richness of this work would not have been realized. Dr. Keoleian deserves special thanks for helping guide me through the process of researching, analyzing and writing this thesis. Also, Dr. Marty Heller provided great support through regular discussions on methodology development and this work's application into future diet-level studies. Finally, Dr. Geoff Lewis was instrumental in using GIS software to generate county-level characterization factors and blue water irrigation values, which was a necessary element in the regional assessment of each crop studied.

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Abstract

Our growing population and increasingly variable climate conditions challenge our ability to meet pressing demands for food, water and energy. With approximately 70% of U.S. freshwater resources applied to agriculture with most withdrawals occurring in water scarce regions, critical analysis is required to determine how regional water use and availability impact user competition for water resources. Aiming to provide insight into the cradle-to-farm gate impacts of different U.S. consumed crops, this thesis begins with a comprehensive literature review to consider the progress and opportunities occurring around water scarcity studies over the last 40 years. Using empirical data and emerging water impact assessment models, a methodology is proposed providing characterization of 10 U.S. consumed crops at regional levels (county, state, and national), resulting in production-weighted water competition footprints for each crop. This analysis also considers water competition footprints of crop imports and exports, which factor into national water footprint values of U.S. consumed crops. Results contrast water use and competition footprint values for select crops at difference spatial scales, indicating the significant impact agricultural processes have in water scarce regions. This research is expected to contribute towards diet-level impact studies, filling gaps where additional life cycle water assessment methods are needed.

1. Introduction

Our growing population and increasingly variable climate conditions are challenging our ability to meet pressing demands for food. As an elemental need for survival, lack of access to clean water can serve as a catalyst for conflict, especially in tense regions already struggling with water scarcity in South and Southeast Asia, Northern Africa, and the Middle East (Reisinger, 2015). With approximately 70% of U.S. freshwater resources applied to agriculture (Koehler, 2008), scientists are seeking systematic and integrated techniques to better understand and quantify the food-energy-water (FEW) nexus in order to develop sustainable solutions to meet the needs of people today and in the future. Exacerbating the issue is the heterogeneous distribution of our freshwater resources, their increasing scarcity and degraded quality, challenging long term FEW system sustainability (Helmstedt et al., 2015). California's recent droughts and corresponding water, food, and energy sector impacts are timely examples that illustrate this concern.

There is an urgent need for methodological approaches to properly account for freshwater-related environmental impacts from agriculture (Koehler, 2008). This is especially important for evaluating the influence of individual diets on these impacts. Many current methodologies are improvements on the original Falkenmark water stress index which compares per capita renewable water resources in a region with regional demand data (Falkenmark, 1989). Though useful as an intuitive metric for water stress, this indicator is limited in its ability to accurately capture smaller spatial differences in water scarcity, infrastructure impacts, or variations in demand between regions (Rijsberman, 2006). Another useful, yet limited, methodology involves assessing water scarcity solely using climate models (Vörösmarty, Green, Salisbury, & Lammers, 2000), but this technique again ignores any human impacts, whether through infrastructure, agriculture, or other demands, drawing on the available freshwater resources.

A significant advancement in life cycle assessment (LCA) water use impact assessment was the water stress indicator (WSI) developed by Pfister et al. (2009) which accounts for water use based on human health, ecosystem function, and damage to local resources (Stephan Pfister, Koehler, & Hellweg, 2009). This method is widely accepted within the LCA community, and is available for use in various LCA software packages including SimaPro, Umberto, and others. This method does have shortcomings since it leaves out considerations for green water flows or resources lost due to degradative freshwater (Stephan Pfister et al., 2009).

An apparent limitation of the WSI emerges when agricultural water use impacts are assessed at an annual scale, failing to account for the seasonality on water demand associated with agricultural processes which is especially prevalent in regions with distinct dry and humid seasons (Payen, Basset-Mens, & Perret, 2015; Tendall, Raptis, & Verones, 2013). However, monthly hydrological and water use data are difficult to attain, requiring use of theoretical models and additional assumptions to supplement data gaps (Payen et al., 2015). There is also lack of consensus about freshwater characterization factors, specifically whether water withdrawal or water consumption are appropriate metrics for determining environmental impacts, and whether groundwater stocks should be considered in freshwater availability calculations (Berger & Finkbeiner, 2013; Anne-Marie Boulay, Ecile Bulle, Bayart, Deschenes, & Ciraig, 2011; Stephan Pfister et al., 2009; Tendall et al., 2013). These are the challenges for which LCA practitioners and researchers have been pursuing solutions, and this thesis offers some possible opportunities to fill these gaps.

Though water stress methodologies have advanced in recent years, there is limited research connecting diet with freshwater use and its regional stresses. Metrics like Nutritional Water Productivity (Renault & Wallender, 2000) provide a general approach and analysis for connecting water use and nutrition, but they fail to incorporate water stress indicators or more regional impact assessments at smaller spatial scales. This thesis seeks to address this gap and propose a useful methodology for assessing watershed-scale agricultural water use impacts as it relates to regional water competition among other users. More specifically, the proposed method will result in water competition footprints for various crops grown and consumed in the U.S., allowing future application in U.S. diet-level studies. These food systems and diet studies can inform water resource policy, and may lead to optimization in the geospatial distribution of crops to meet growing food demand while minimizing use and impacts of our limited freshwater resources.

Water impact assessment methods in LCA have been developed over the last three decades in an attempt to evaluate water resource vulnerability and impacts (Brown & Matlock, 2011). The water utilization level is one of the earliest accepted water scarcity assessment methods which evaluates available regional runoff for human use (Falkenmark, 1989). Many methods have evolved and expanded on this concept, most using either a withdrawal-to-availability or consumption-to-availability ratio as the basis for resulting stress calculations (Berger & Finkbeiner, 2013). In the last decade, significant effort has gone towards developing a standardized water footprint assessment methodology, allowing practitioners to quantify the potential environmental impacts of a product or process as they relate to water (ISO, 2014). These water footprint methods (Baitz et al., 2014; Anne-Marie Boulay et al., 2011; Ecoinvent, 2007; Kounina et al., 2013; Vionnet, Lessard, Offutt, Levova, & Humbert, 2012) classify input and output water flows according to watercourse, quantity, quality, and geographic and temporal dimensions (Berger & Finkbeiner, 2013; ISO, 2014).

As seen in Figure 1, U.S. Geological Survey (USGS) freshwater use data indicates that agriculture use of freshwater in the United States dominates total freshwater withdrawals. Intensity of freshwater use is particularly prevalent in the western United States, an area prone to greater water scarcity compared to other parts of the nation. Research findings by Averyt et al. (2013) validate this finding (Figure 2), indicating intense agricultural water use in Western U.S. leading to increased stress of regional water supplies. This highlights the importance of developing a water use assessment methodology to evaluate the regional water impacts of U.S. grown crops, forging an opportunity to relate crop water footprints to individual U.S. diets.

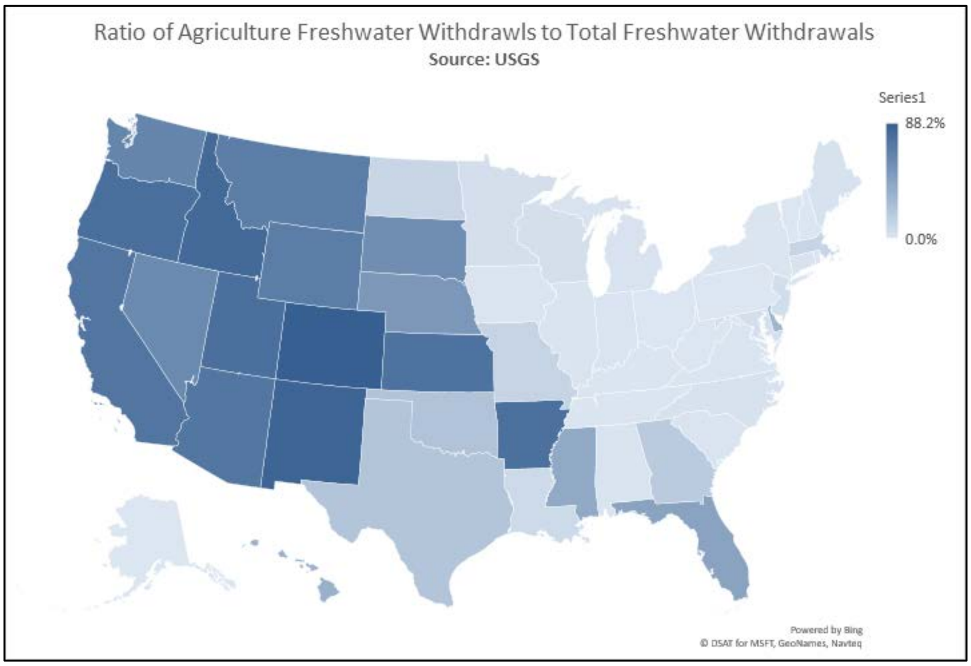


Figure 1: U.S. map depicting intensity of freshwater use for agriculture in U.S. states.

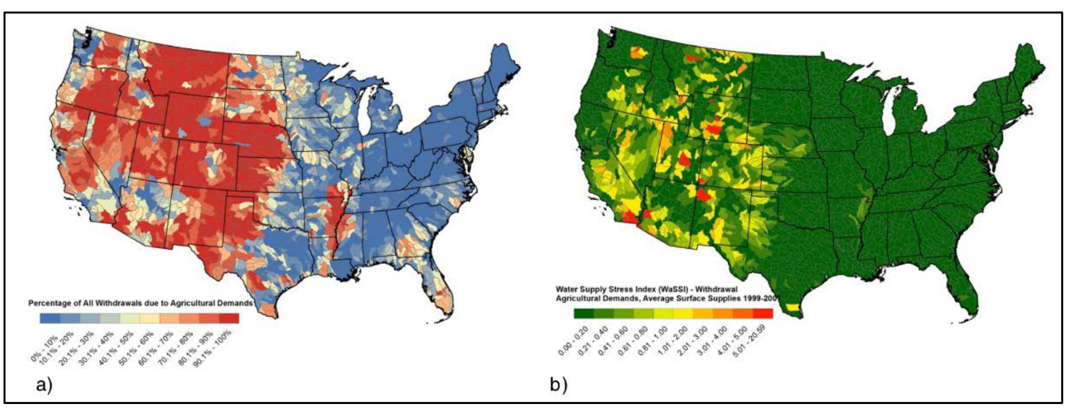


Figure 2: The agricultural contribution to the Water Supply Stress Index (WaSSI) for average supplies 1999-2007. (a) Percentage of total withdrawal demands by agriculture for each HUC-8 watershed; (b) WaSSI based only on agricultural demands (Averyt et al. 2013)

2. Literature Review

In order to develop or apply a proper methodology to regionally characterize water use for agricultural processes, an in-depth literature review was conducted to identify the prevailing methods used in LCA today. This review provided opportunity to determine which methodologies best meet the needs of this study, and helped identify shortcomings in each methodology which may be improved in future studies. Also, available primary data sources were investigated to determine applicable and useful data for integration into a proposed method, and to support and validate any results.

The purpose of this thesis is to develop characterization factors for assessing regional freshwater consumption from agricultural crop production, with no attempt made to determine mid- or endpoint impacts within any of the three areas of protection: human health, ecosystem quality, and resources. However, midpoint categories are discussed to determine possible application in future studies. Application of the proposed characterization factor methodology may allow assessment in mid- or endpoint impact categories, but is outside the scope of this thesis.

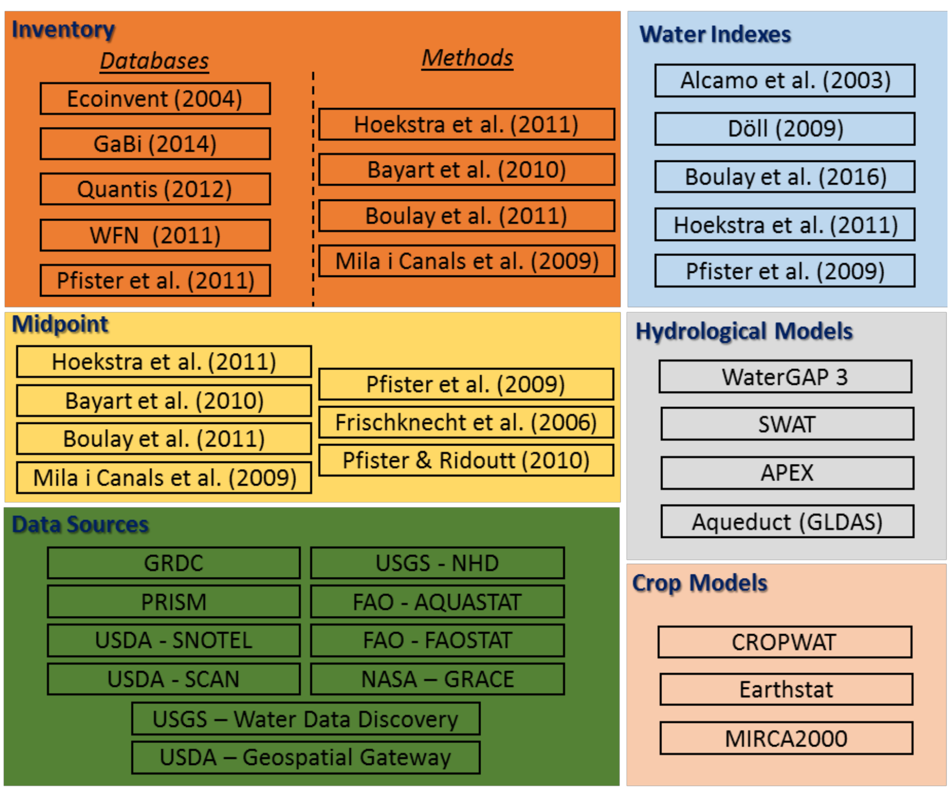


Figure 3: Water impact assessment tools and methods for LCA of agricultural processes. Partially adapted from Kounina et al. (2013)

In recent years, multiple studies have provided comprehensive evaluation of different water impact methodologies for application in LCA (A.-M. Boulay et al., 2015; A. M. Boulay et al., 2015; Brown & Matlock, 2011; Jeswani & Azapagic, 2011; Kounina et al., 2013; Sala, Benini, Castellani, Vidal-Legaz, & Pant, 2016). These studies examined all aspects of water inventory databases and methods, mid- and endpoint methodologies, and water indices used to characterize water use based on specific geographic and temporal dimensions. For use in agricultural process studies, certain methods and sources were considered most relevant and useful for future LCA studies (Figure 3).

2.1 Terminology

Key terminology used throughout this thesis are defined in Table 1.

Table 1: Water characterization and LCA terminology

Term	Definition	Source
Water Use	Any use of water for human activity. This includes water withdrawals, water releases, or any other human activities within a drainage basin.	(ISO, 2014)
Water Consumption	Represents freshwater withdrawals which are evaporated, incorporated in products and waste, transferred into different watersheds, or disposed into the sea after usage.	(Falkenmark & Rockstrom, 2004)
Water Withdrawal	Any off-stream anthropogenic use of water. Includes any temporary or permanent water removal from any water body or drainage basin.	(ISO, 2014; Pfister, Koehler, & Hellweg, 2009)
Freshwater Quality	A set of parameters considered to characterize the chemical, physical, and biological properties of freshwater.	(Berger & Finkbeiner, 2013)
Virtual Water	Amount of water evaporated in the production of, and incorporation into, agricultural products, neglecting runoff.	(Allan, 1993, 1994; Stephan Pfister et al., 2009)
Degradative Use	Describes a quality change in water used and released back to the same watershed, and requires a description of inputs and outputs in the inventory analysis.	(Pfister et al., 2009)
Blue Water	Surface and groundwater sources (lakes, rivers, aquifers).	(Hoekstra, Chapagain, Aldaya, & Mekonnen, 2009)
Green Water	Water held in the soil in the form of soil moisture.	(Hoekstra et al., 2009)
Gray Water	The volume of freshwater that is required to dilute polluted water to existing ambient water quality standards.	(Hoekstra et al., 2009)
Water Scarcity	Water use approaching or exceeding the natural regeneration of water in a given area, e.g., a drainage basin.	(Berger & Finkbeiner, 2013)
Water Stress Index (WSI)	Ratio of total annual freshwater withdrawals to hydrological availability. WSI values enable LCA practitioners to effectively characterize and normalize water impacts across in regions spanning possible climatic conditions, providing a useful framework for assessing the water impacts of products.	(Pfister et al., 2009)
Marginal Water Use	Water consumed in a process or product that accounts for a marginal level of consumption when compared to total water consumed in the region. No standard is established to determine marginal vs. non-marginal water use. This thesis considers any process consuming more than 5% of regional water consumption non-marginal.	(A. Boulay et al., 2016)
Water Competition Footprint	Potential environmental, human health and resource impacts related to water due to a process, product or system. This serves as a midpoint category in LCIA to characterize regional water deprivation impacts of a process as it relates to available regional water supplies and user requirements (environmental and human).	(ISO, 2014; Stephan Pfister et al., 2009a)

2.2 Databases

Databases containing water use inventory data are numerous, many receiving widespread adoption due to their ease of use and general application within LCA. The most widely known and applied databases for water use impacts are Ecoinvent, GaBi, Quantis, Water Footprint Network (WFN), and Pfister et al. (2011) (Kounina et al., 2013).

Ecoinvent provides both elementary and non-elementary flows, and distinguishes between different surface water sources, groundwater, and water applied in industrial processes (termed turbined water) (Ecoinvent, 2007; Frischknecht et al., 2004; Kounina et al., 2013). Though each database process carries certain location information providing spatial differentiation, input water quality and siting of output water are not considered (Kounina et al., 2013).

The GaBi database has embedded within its LCA software with data covering surface and groundwater flows, ocean/sea salt water and water used for energy generation (hydroelectric). GaBi does not consider degradative water use in its blue water calculations (Baitz et al., 2014). Water flows considered in GaBi include elementary freshwater (river/lake/groundwater), fossil groundwater, surface run-off, tap water, untreated wastewater, water vapor, evapotranspiration, technosphere resource flows, and brackish water (Baitz et al., 2014). Input flows include ground, lake, rain, river and sea water (Koehler & Thylmann, 2014). Output flows include evapotranspiration and water vapor, as well as water (both freshwater to lakes and rivers and saltwater to oceans/seas) emissions into lakes and rivers including cooling water, rain water, turbined water, and wastewater (Koehler & Thylmann, 2014). Turbined water is water used in hydro energy generation (Koehler & Thylmann, 2014).

The Quantis Water Database, an improvement to Ecoinvent, segregates all flows into inputs and outputs and uses a water balance for final assessment (Quantis 2012). Quantis is aimed at providing additional specificity to Ecoinvent's eight generic flows (Table 2) covering various water uses, providing LCA practitioners with additional input and output water flows for easier application within different water impact methodologies (Kounina et al., 2013; Vionnet et al., 2012). Location information is incorporated into each database process to enable spatial differentiation. All input and output flows assessed in the Quantis Water Database can be found in Table 3.

Table 2: Ecoinvent 2.2 Flows (Ecoinvent, 2007)

Flow Types
Cooling water
Lake Water
River Water
Ocean Salt Water
Sole Salt Water
Water, Unspecified Origin
Ground Water (from well)
Water for turbine use

Table 3: Quantis Water Database Flows (Vionnet et al., 2012)

Input Flows	Output Flows
Ground Water, Depleted, Shallow	Water, Turbined Use
Groundwater, Depleted, Other	Water Consumed, from Turbine Use
Groundwater, Fossil	Surface Water
Groundwater, Non-Depleted, Shallow	Groundwater
Groundwater, Non-Depleted, Other	Water Consumed, Evaporated, Fresh
Surface Water (Lake, River, etc.)	Water Consumed, Incorporated, Fresh
Water, for Turbine Use	Water Evaporated, from Nature
Water, Naturally Occurring	Water, Return Flow to Nature
Salt Water	Salt Water, Consumed
	Salt Water

The Water Footprint Network (WFN) developed by Hoekstra et al. (2011) uses the virtual water concept to determine inventory flows for a wide array of products and processes including crops, fuels, and livestock (Hoekstra, Chapagain, Aldaya, & Mekonnen, 2011). This database considers blue, green, and gray water inventory data for each product and publishes water footprint values for products and processes at the national level (Hoekstra et al., 2011). It is important to recognize the use of the term "water footprint" within the WFN does not coincide with the term definition outlined in ISO 14046 (B. Ridoutt et al., 2015; ISO, 2014)

Pfister et al. (2011) developed a database assessing the water consumption for 160 crops at the country level (Stephan Pfister, Bayer, Koehler, & Hellweg, 2011). This database provides WSI-weighted water consumption values reported as RED (Relevant for Environmental Deficiency) water, which includes consideration for full-irrigation water consumption, deficit water consumption and expected water consumption (Kounina et al., 2013; Stephan Pfister et al., 2011).

Databases continue to improve, but still lack specificity in abstracted water sources (e.g. surface, unconfined aquifer, confined aquifer) and characterization (Kounina et al., 2013). Specifically, existing databases should be completed with input/output freshwater flow differentiated according to water types based on its origin, region of withdrawal, and characterized with a set of quality parameters (Berger & Finkbeiner, 2013). Due to the complexity and significance of assessing agricultural processes regionally, as well as properly tuning the temporal scale of data used for assessment, databases must move towards incorporating more granular input and output information about water use for different processes (e.g. type of water, quantity, location of abstraction, water source, etc.) if hoping to deliver the level of confidence provided by more direct inventory methods.

2.3 Inventory Methods

The Water Footprint Network (WFN) (Hoekstra et al., 2009) reports the virtual water consumed and polluted during the production of a product, or throughout a process. It covers all three water types including blue, green, and gray water (i.e. degradative water). Values are primarily used as a water inventory, and application towards assessing impacts for LCA, though possible, are challenging. The term “water footprint” has different definitions depending on the practitioner and their applied methodology. “Water footprint” as defined by Hoekstra does not consider regional water stresses or whether water consumption of a product or process denies other users of water. This differs with other LCA methodologies, specifically Pfister and Ridoutt (B. G. Ridoutt & Pfister, 2010), who indicate these considerations should exist within water footprint methodologies.

Bayart et al. (2010) proposed a methodology for assessing off-stream water use of a product or process for use in LCA. Off-stream water use is defined as water used which is removed from a surface or groundwater source (Bayart et al., 2010). This methodology provides increased specificity in the life cycle inventory (LCI), proposing that inventory flows be identified based on their resource type (e.g. groundwater, surface water), each receiving specific characterization factors.

Boulay et al. (2011) provide an inventory method which builds on Bayart et al. (2010), by adding eight water quality levels for each resource and including rain water. In total, the methodology developed 17 water categories based on source, quality and potential users (Anne-Marie Boulay et al., 2011). With degradative water use not assessed in this level of detail in previous inventory methods, Boulay et. al (2011) filled a gap in life cycle impact assessment (LCIA) by providing the elementary flows needed to evaluate how degradative return flows translate to lost functionality to human users (Boulay et al., 2011).

Mila I Canals et al. (2009) differentiates between types of water use in LCI and provides two impact pathways for LCIA: freshwater ecosystem impact (FEI) and freshwater depletion (FD) (Milà I Canals et al., 2009). This method proposes differentiating between inputs of green water (soil moisture), blue water (ground and surface water), fossil blue water (non-renewable groundwater), and water use due to land use changes. To accomplish this, water inventory data should be categorized into ‘evaporative’ and ‘non-evaporative’ use (read, ‘water use’ and ‘water consumption’ (Owens, 2001)). Other than WFN, this is the only method which considers land use change as it relates to water availability and distinguishes between fossil and renewable groundwater (Kounina et al., 2013).

2.4 Midpoint Assessment Methods

The Ecological Scarcity Method (Frischknecht, Steiner, Arthur, Norbert, & Gabi, 2006) provides eco-factors for a range of substances expressing their environmental impact. This method simply multiplies elementary flows by their corresponding eco-factors. Results are expressed in eco-points and then aggregated to a single-score indicator expressing the overall environmental impact. There is no characterization (conversion of LCI flow to the common unit of the impact category) performed (i.e., water is not characterized according to quality or type of water source) (Kounina et al., 2013). Normalization occurs via assigning one (1) eco-point to the total annual freshwater withdrawal for human use in a specific region. The method uses a political distance-to-target weighting procedure in which the ratio of a current flow (F) to a critical flow (F_c) needs to be determined. Critical flows are derived from legislative targets and political goals, not from assessment of ecological necessity for water (Frischknecht et al., 2006). This method aims to identify deviations of water use from political targets and is not intended for use in assessing ecological damage from water use.

$$Eco-Factor\left[\frac{\text{eco-points}}{\text{Unit}}\right] = \underbrace{K}_{\substack{\text{Characterization}\\ \text{(Optional)}}} \times \underbrace{\frac{1\ eco-point}{F_n}}_{\text{Normalization}} \times \underbrace{\left(\frac{F}{F_c}\right)^2}_{\text{Weighting}} \times \underbrace{c}_{\text{Constant Factor}}$$

The square of the weighting factor leads to an above average weighting if the critical flow is significantly exceeded. Thus, the weighting factor is dependent on the withdrawal-to-availability (WTA) ratio and can range from 0.0625 to 56.3 (Table 4). Multiplying the result by the constant c (10^{12}/a) leads to a more convenient dimension.

$$Weighting = \left(\frac{\text{Current Flow}}{\text{Critical Flow}}\right)^2 = \left(\frac{\text{Total Annual Fresh Water Withdrawal For Human Uses } (W)}{\text{Annually Available Renewable Water Supply } (A) \times 20\%}\right)^2 = (WTA)^2 \times \left(\frac{1}{20\%}\right)^2$$

Table 4: WTA ranges and weighting factors assuming Fc = 20% of renewable water supply. Adapted from Frischknecht et al. (2006)

WTA		WTA used for Calculation	Weighting Factor
Low	< 0.1	0.05	0.0625
Moderate	0.1 < 0.2	0.15	0.563
Medium	0.2 < 0.4	0.3	2.25
High	0.4 < 0.6	0.5	6.25
Very High	0.6 < 1.0	0.7	16.0
Extreme	> 1.0	1.5	56.3

Pfister et al. (2009) developed a commonly used water stress impact metric in the form of a water stress index (WSI). This method only considers blue water (omitting green or gray water) and consumptive water use (not withdrawals), and relies on the WaterGAP global model for determining water availability in regions undergoing assessment. The proposed equation for determining water stress index (WSI) in a region is:

$$WSI = \frac{1}{1 + e^{(-6.4 \times WTA)} \times \left(\frac{1}{0.01} - 1\right)}$$

The withdrawal to availability ratio (WTA) aggregates the water consumption for each activity and user in a watershed (WU_{ij}) over the total water availability (WA_i) in the studied watershed.

$$WTA_i = \frac{\sum_j WU_{ij}}{WA_i}$$

WTA_i = WTA in Watershed i
WA_i = Watershed i availability
WU_{ij} = Withdrawals for different users j

The WTA was further refined to consider increased effective water stress caused by strongly regulated flows (SRF) in a watershed (Nilsson et al.) in the form of dams or other river regulating systems. A variation factor (VF), which is derived from the standard deviation of the precipitation distribution, was added to capture these flows. VF is defined as the aggregated measure of dispersion of the multiplicative standard deviation of monthly (s^*_{month}) and annual precipitation (s^*_{year}) (Stephan Pfister et al., 2009). Pfister's data relied on geographic information system (GIS) software allowing data processing and statistical evaluation at different spatial resolutions. With Pfister's model utilizing a grid-based GIS system, VFs for each grid within a watershed are calculated and aggregated with precipitation data to determine a watershed's total variation factor (VF_{WS}) before incorporation into the Water Stress Index.

$$WTA_i = \frac{\sum_j WU_{ij}}{WA_i}$$

$$VF_{WS} = \frac{1}{\sum P_i} \sum_{i=1}^{n} VF_i \times P_i$$

$$WTA^* = \begin{cases} \sqrt{VF} \times WTA \text{ for SRF} \\ VF \times WTA \text{ for non-SRF} \end{cases}$$

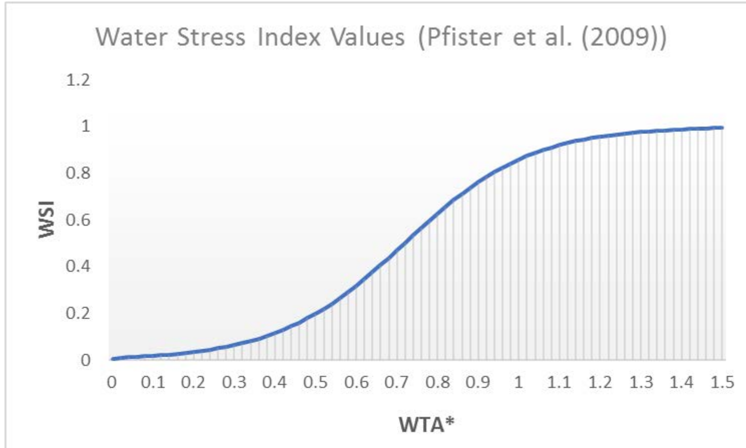


Figure 4: WSI values based on WTA (Pfister et al. 2009)*

The WSI curve forms a logistic function (Figure 4) which is tuned to result in a WSI of 0.5 for a WTA of 0.4, which is the threshold between moderate and severe water stress (when applying the median variation factor of all watersheds, VFmedian = 1.8, WTA* = 0.72). The full range of WSI values fall between 0.01 and 1. This method goes further to assess damages to certain areas of protection (AoP) including human health, resources and ecosystem quality, but in its purest form serves as a screening indicator or characterization factor in LCIA. Unlike the WFN, Pfister does not identify values as "water footprint" until after the WSI has been applied, meaning inventoried water values have been characterized based on regional water availability and consumption. This scarcity weighted water footprint is further developed by Ridoutt and Pfister (2010).

Hoekstra et al. (2011) (WFN) characterizes each water type (blue, green, gray) with separate scarcity indexes which are disaggregated, allowing each water type to be applied individually to each area of protection (human health, ecosystem quality, and resources) (Kounina et al., 2013). Ratios of water consumption (termed 'water footprint') to availability are used for blue and green water indexes, while the gray water pollution index considers the ratio of total gray water consumption in the region to runoff.

Boulay et al. (2011) proposed a scarcity indicator based on their endpoint model for human health (Anne-Marie Boulay et al., 2011; Kounina et al., 2013). The surface water parameter is based on the CU/Q90 ratio proposed by Döll (2009). Total CU (consumed water) in the region is calculated using WaterGAP. Q90 is called the "statistical low flow," representing the flow that is exceeded nine months out of ten (Anne-Marie Boulay et al., 2011). The stress index range is similar to Pfister et al. (2009a) with values between 0 and 1.

Mila i Canals et al (2009) identified that impact pathways resulting from water use include water use leading to insufficient freshwater availability impacting human health, and land use changes leading to changes in freshwater availability having effects on ecosystem quality (termed Freshwater Ecosystem Impacts (FEI)). Fossil and aquifer groundwater use above renewability rates results in reduced availability of freshwater as a resource for future generations (termed freshwater depletion (FD)). This assumes that the only consumption of water from aquifers (evaporative use) and fossil water (evaporative and non-evaporative use, (ISO, 2014)) can contribute to that impact category. In order to provide characterization factors (ADP_i) (factors converting the LCI flow to the common unit of the impact category) the method of Guinée et al., (2001) was used to determine the depletion of abiotic resources:

$$ADP_i = \frac{ER_i - RR_i}{(R_i)^2} \times \frac{(R_{SB})^2}{DR_{Sb}}$$

$ADP_i = Abiotic\ Depletion\ Potential\ of\ water\ resource\ i$
$ER_i = Extraction\ Rate\ of\ Water\ Resource\ i$
$RR_i = Regeneration\ Rate\ of\ Water\ Resource\ i$
$R_i = Ultimate\ Reserves\ of\ Water\ Resource\ i$
$R_{Sb} = Ultimate\ Reserves\ of\ the\ Reference\ Resource\ Antimony$
$DR_{Sb} = Deaccumulation\ Rate\ of\ Antimony$

Water use leading to insufficient freshwater availability effects ecosystem quality (termed freshwater ecosystem impacts (FEI)). This aspect of the method aims to assess the ecological consequences of water use in a certain region. Consumption of fossil blue water is excluded as it fulfills minimal ecological functions. Only the evaporative use of blue water (surface water and unconfined aquifers) as well as water use due to land use changes are taken into account. FEI uses a water stress indicator (WSI) developed by Smakhtin et al. (2004) as a characterization factor:

$$WSI_i = \frac{WU_i}{WR_i - EWR_i}$$

$$WUPR_i = \frac{WU_i}{WR_i}$$

$WSI_i = Water\ Stress\ Indicator\ of\ Water\ Resource\ i$
$WU_i = Total\ Use\ of\ Water\ Resource\ i$
$WR_i = Renewable\ Water\ Reserves\ of\ Water\ Resource\ i$
$EWR_i = Environmental\ Water\ Requirement\ in\ the\ Region$

The basis for this indicator is the water use per resource indicator (WUPR) (Raskin, Gleick, Kirshen, Pontius, & Strzepek, 1997), which relates the total water use to the renewable water reserves in a region. The WSI enhances the WUPR or WTA indicator by reserving a certain amount of freshwater necessary to sustain the ecological functions in a particular region. Depending on the local water scarcity and the respective ecosystem demand, site specific characterization factors are obtained assessing the severity of additional human water use.

2.4.1 Shortcomings of midpoint impact methods

Proper terminology is a challenging aspect of these different methods, each borrowing some terms from other methods while also creating new ones. Some terms add additional layers to existing ones, while others are redefinitions with minor changes. An example is water use and water consumption (Owens, 2001). The publication of ISO 14046 in 2014 helped drive agreement between different methods and should significantly improve user application and interpretation moving forward.

Optimal inventory data should include information regarding water source (surface, unconfined groundwater, fossil groundwater), region (sub-basin or basin), water quantity abstracted, time (month), type of use (turbined, consumptive, degradative, cooling), amount of water discharged back into the basin, and water quality upon return (Tendall et al., 2013). Ideally, each water type would have individual characterization factors based on the climatic, geographic and consumption specifics of the region of abstraction. Due to the effort and likely inability for researchers to acquire this level of data for products or processes, especially if trying to assess a product produced over geographically-diverse regions and temporally-variant horizons, minimum standards for inventory data should include water quantity, water source, region, and water discharged. However, confidentiality of water inventory data remains a challenge (Tendall et al., 2013).

These methods, though increasing in complexity and completeness, have not yet been measured against empirical evidence linking water scarcity, water deprivation and impact on each area of protection (Berger & Finkbeiner, 2013). Additionally, water scarcity indices should be viewed alongside impact assessment indicators to allow more thorough and informed interpretation of freshwater use impacts (Berger & Finkbeiner, 2013). Similarly, model uncertainty and input data uncertainty still require evaluation and documentation (Berger & Finkbeiner, 2013), and the quantification of impact pathways leading to human health and ecosystem damages is required to understand the full range of environmental effects (Koehler, 2008).

When applying these different methods, practitioners are faced with trade-offs and embedded assumptions that are not easily identifiable, possibly leading to the use of midpoint impact methods not compatible with collected inventory data (Tendall et al., 2013) or ideally suited for the study at hand (Berger & Finkbeiner, 2013). This highlights the need for inventory data to be developed alongside impact assessment methodologies to ensure consistency (Tendall et al., 2013). A simple, but important, distinction is whether a method employs an attributional or consequential LCI approach (Berger & Finkbeiner, 2013).

Freshwater use, being a regional asset with the complex impacts of scarcity and deprivation felt primarily within a watershed, basin or sub-basin, must be regionally characterized due to the site-specific local impacts of freshwater abstraction (Koehler, 2008; Payen et al., 2015; Tendall et al., 2013). Up-scaling to broader spatial coverage should be avoided (Tendall et al., 2013), as impact assessment broader than watershed level may lead to inaccurate results. LCIA of water use must be understood in the context of the geographically diverse and time-variant character of freshwater resources (Koehler, 2008), and studies should include varying spatial resolutions and temporal ranges to provide a comprehensive assessment of water use impacts within a region.

Some WSI values are calculated on an annual scale, which fail to properly assess regions with distinct dry and wet seasons, a factor critical for assessment of agricultural water use (Payen et al., 2015). Beyond temporal scale, WSI should incorporate changes in water availability over time, especially when considering fossil groundwater reserves not subject to surface recharge or other flows. Reliance on groundwater in arid regions gives it a disproportionate weighting when calculating regional water stress, so annual changes in fossil groundwater abstraction and availability should be incorporated into WSI calculations. In general, most methods fail to incorporate fossil groundwater depletion into their calculations (Kounina et al., 2013), likely due to lack of available data (Stephan Pfister et al., 2017).

2.5 Water Indexes

Water indexes act as characterization factors for water use based on regional considerations. Elements included in water index calculations include water availability, water use, and water consumption or withdrawal. The indexes developed by Boulay (Anne-Marie Boulay et al., 2011), Pfister (Stephan Pfister et al., 2009) and Hoekstra (WFN) (Hoekstra et al., 2011) are the same as those explained in the mid-point indicators above, and will not be restated in this section.

Alcamo et al. (2003) developed the criticality ratio and criticality index, helping form the basis for later, more comprehensive, methodologies. The criticality ratio measures total water use to availability, with values ranging from near 0 to greater than 1 (Joseph Alcamo et al., 2003; Kounina et al., 2013). Water uses considered include agriculture, industry and households. The criticality index compares the criticality ratio with a region’s per capita water availability, displayed in Table 5 outlining four criticality indexes: water surplus, marginally vulnerable water resource, water scarcity, and severe water scarcity (Joseph Alcamo et al., 2003). The criticality ratio is a basic element included in nearly all water index calculations and methodologies (Berger & Finkbeiner, 2010; A. Boulay et al., 2016; Milà I Canals et al., 2009; Stephan Pfister et al., 2009; B. G. Ridoutt & Pfister, 2010), the primary exception being Hoekstra et al. (2011). However, the criticality index did not gain much momentum as an indicator in these types of water assessments (Näf, 2008).

Table 5: Criticality Index (Alcamo et al. 2003). Adapted from Kulshreshtha (1993)

	Criticality Ratio (Use / Availability)			
Water Available (per capita) [m3/(cap.yr)]	Water Surplus < 0.4	Marginal Vulnerability 0.4 - 0.6	Water Scarcity 0.6 - 0.8	Severe Water Scarcity > 0.8
< 2,000	2	3	4	4
2,000-10,000	1	2	3	4
> 10,000	1	1	2	4

1 = water surplus
2 = marginally vulnerable
3 = water scarcity
4 = severe water scarcity

Döll (2009) uses WaterGAP at a 0.5^{o} x 0.5^{o} resolution to calculate groundwater recharge, total runoff and river discharge (Döll, 2009). The water scarcity indicator is the ratio of the consumptive water use (CU) to the statistical low flow Q90 in each 0.5^{o} grid cell (Döll, 2009). Each element is calculated on a monthly basis. The water scarcity indicator is then combined with the Human Development Index (HDI) for each region/country to form a sensitivity indicator. By combining the calculated sensitivity indicators with modeled groundwater recharge rate decreases, Döll (2009) was able to estimate the vulnerability to the impact of decreased groundwater recharge in 2050 (Kounina et al., 2013).

2.5.1 New Standard for LCA Water Use Indexes

Water characterization has undergone significant research and revision, especially over the last decade. In 2007, the UNEP-SETAC Life Cycle Initiative founded Water Use in LCA (WULCA) in an attempt to develop a consensual and operational method for evaluating water use in LCA. This effort, led by Dr. Anne-Marie Boulay and Dr. Stephen Pfister, included a comprehensive literature review (Kounina et al., 2013), a proposed framework for evaluating water use in LCA (Bayart et al., 2010), and methods for characterizing water use and its resulting environmental impacts. The outcome of this effort was AWARE (Available WAter REmaining), a new water scarcity footprint indicator which describes potential water deprivation in a region based on water remaining after human and ecosystem needs are met (A. Boulay et al., 2016). This method assumes that less water remaining within an area after human and ecosystem requirements are met leads to deprivation among other users within the same area (A. Boulay et al., 2016).

Additionally, this effort contributed to and shaped the draft standard ISO DIS 14046 on water footprinting published in 2014, which further standardizes this water impact assessment method within the LCA community.

The AWARE method begins by determining the remaining available water within a region after all human and ecosystem requirements are met (A. Boulay et al., 2016). First, water Available Minus the Demand (AMD) is calculated for both humans and aquatic ecosystems (m^3 m^{-2} $month^{-1}$). Then the value is normalized with the world average AMD (AMD_W = 0.0136 m^3 m^{-2} $month^{-1}$) which is calculated as a consumption-weighted average. Then the value is inverted to represent the surface-time equivalent to generate unused water within the assessed region, with values ranging from 0.01 to 100 (Figure 5) (A. Boulay et al., 2016). A value of 1 indicates the available water within the region is equal to the global average, and larger values indicate greater regional water scarcity compared to the global average (A. Boulay et al., 2016).

The WaterGAP model is used to determine availability within the assessed region, averaging values over a 50-year timeframe (1960-2010) (Joseph Alcamo et al., 2003; Müller Schmied et al., 2014). Human consumption is also modeled in WaterGAP (Flörke et al., 2013) and assessed in the year 2010, and ecosystem demand is assessed using the Variable Monthly Flow (VMF) method (Pastor, Ludwig, Biemans, Hoff, & Kabat, 2014). Since agriculture uses water in regions and during months differing from industrial and domestic uses, different characterization factors are provided for agricultural and non-agricultural use (A. Boulay et al., 2016).

$$AMD = Availability - Consumption_{Human} - Demand_{Ecosystem} \left(\frac{m^3}{m^2 month}\right)$$

$$\text{Water Scarcity Footprint} = \text{Water Consumption (Inventory)} \times \frac{1}{\frac{AMD_W}{AMD}}$$

$$\text{Characterization Factor } (CF) = \frac{1}{\frac{AMD_W}{AMD}}$$

AWARE is currently under peer review, and is expected to serve as the standardized method for water use assessment in LCA. Due to this reason, AWARE characterization factors were used in the methodology later demonstrated in this thesis.

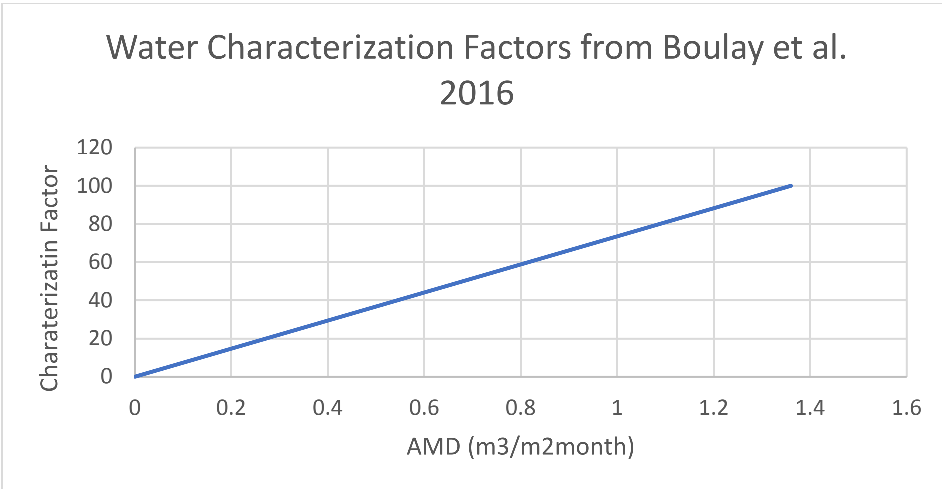


Figure 5: Water Characterization Factors from Boulay at al. 2016

2.6 Hydrologic Cycle Models

WaterGAP serves as one of the most widely used hydrologic models in life cycle assessment. WaterGAP has undergone multiple updates and revisions, with WaterGAP 1.0 first introduced in Alcamo et al. (1997), WaterGAP 2.1 explained and tested in Döll et al. (2003) and Alcamo et al. (2003), and WaterGAP 2.2 described in Müller Schmied et al. (2014). The most recent version (WaterGAP3) operates at a 5 arc-minute resolution and consists of three sub-models (Figure 6) including: 1) a water balance model simulating terrestrial water flows, 2) a water withdrawal model calculating water withdrawals and consumption into agricultural irrigation processes, livestock production, domestic use and small businesses, manufacturing, and thermal electricity generation (methodologies for each provided in Table 6), and 3) a water quality model estimating degradative water flows due to sector activity (Voss, Voss, Bärlund, & Alcamo, 2009). This model provides outputs at the 0.5 arc minute resolution, and is the only available hydrological model that is calibrated to actual river discharge measurements, better reflecting reality over other models (A. M. Boulay et al., 2015). Included water balance elements are in Figure 7.

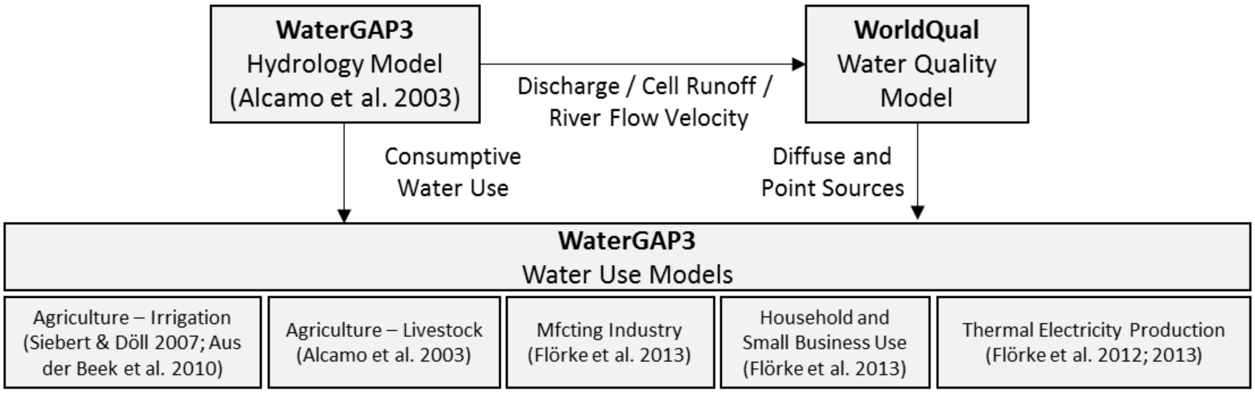


Figure 6: WaterGAP sub-model interactions. Adapted from (Voss et al., 2009).

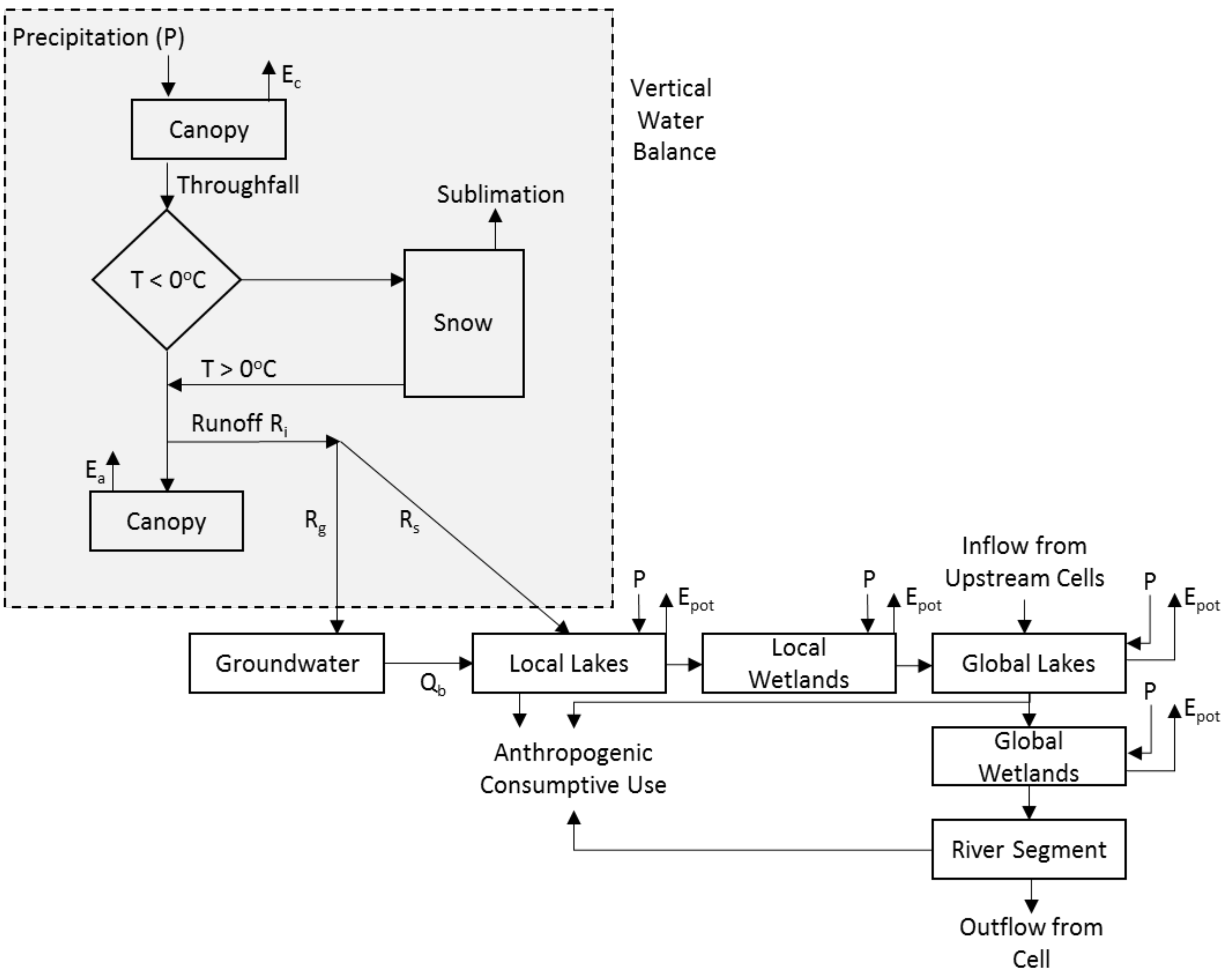


Figure 7: WaterGAP 3 water balance: R_g (groundwater recharge), R_s (surface runoff), R_l (runoff generated on land), E_{pot} (potential Evaporation), E_a (actual evaporation), E_c (canopy evaporation), Q_b (Surface Runoff). Adapted from (Joseph Alcamo et al., 2003)

Table 6: Water use sub-sector methodologies within the WaterGAP model.

Sector	Methodology Summary	Sources
Agriculture – Irrigation	Digital global maps identify irrigated areas and irrigation requirements based on growing seasons and cropping patterns for 21 crop types. Outputs are computed as net and gross irrigation requirements, which are synonomous with "consumption" and "withdrawal", respectively. Growing seasons are calculated as the optimal 150-day period within a grid based on temperature and precipitation data. Crop-specific evapotranspiration (i.e. consumption) is compared with plant-available precipitation data, the difference resulting in the irrigation requirement. The crop coefficient varies between 0.1 and 1.2, and depends on crop type and growing stage. Plant-available precipitation is the amount of precipitation available for plant uptake, and is computed using the USDDA Soil Conversion Method (similar to CROPWAT).	(Joseph Alcamo et al., 2003; Aus Der Beek et al., 2010; Siebert & Döll, 2007; Smith, 1992)
Agriculture – Livestock	Model multiplies the number of livestock per grid cell, computed on a global grid at 5 arc-minute resolution (GlobalARC),by specific water intensity values for various livestock species. The model considers 10 types of livestock. Water withdrawals for livestock are assumed to be equal to animal consumptive use.	(Joseph Alcamo et al., 2003; GlobalARC, 1996)
Manufacturing Industry	The manufacturing metric gross value added (GVA) is used as the water demand driver for this sector's water withdrawals. National and international statistics and environmental reports from 2005 provide basis for the calculation of country-specific manufacturing structural water use intensities (MSWI), which represents the ratio of manufacturing water consumption per GVA. A technological change factor is also incorporated into the calculation. In general, as structural and technological advancements occur, less water is consumed in this sector. Manufacturing water consumption is calculated using consumptive water use coefficients from Shiklomanov (2000).	(Dziegielewski, Sharma, Bik, Margono, & Yang, 2002; Flörke et al., 2013; Flörke & Alcamo, 2004; Shiklomanov I. A., 2000)
Domestic Household and Small Business Use	National statistics and reports provide estimated national water consumption based by multiplying a national domestic water use intensity (m^3 $capita^{-1}$ $year^{-1}$) by the population. Consumptive-use coefficients (i.e. consumption-to-withdrawal ratio) from Shiklomanov (2000) provide domestic water consumption values. Water use intensities are calculated as a function of structural (i.e. income level) and technological advancements within a country. Data is spatially allocated to specific grid cells based on urban population and population density patterns.	(Flörke et al., 2013; Flörke & Alcamo, 2004; Shiklomanov I. A., 2000)
Thermal Electricity Production	Model calculates the volume of water withdrawn and consumed for thermoelectric power plant cooling, with primary degradative effects being thermal pollution. Power plant size, location, and water intensity is sourced from the World Electric Power Plants Data Set of the Utility Data Institute. The Energy Information Administration (EIA) provides total electricity produced by thermal power plants. Power station water intensity is multiplied by annual thermal electricity production resulting in total water withdrawals for cooling.	(EIA, 2012; M. Flörke, Bärlund, & Kynast, 2012; Martina Flörke et al., 2013; UDI, 2004; Vassolo & Döll, 2005)

The Soil and Water Assessment Tool (SWAT) provides basin-scale impact predictions of management on water, sediment and agricultural chemical yields (P. P. W. Gassman, Reyes, Green, & Arnold, 2007). Model components include "weather (updated daily), hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management" (P. P. W. Gassman et al., 2007). This model outperforms the WaterGAP model in that its spatial resolution allows division of watersheds into multiple sub-watersheds, and can further be divided into hydrologic response units (HRUs). HRUs are unique in their representation of land use, management, and soil practices within their designated watershed (P. P. W. Gassman et al., 2007). When seeking to more accurately account for spatial variability in water use at the sub-basin scale, SWAT outperforms other models including WaterGAP (Scherer, Venkatesh, Karuppiah, & Pfister, 2015).

The Agricultural Policy/Environmental eXtender (APEX) model (P. Gassman & Williams, 2009; Liu, Liu, & Yang, 2016) is "capable of simulating management and land use impacts for whole farms and small watersheds" (P. Gassman & Williams, 2009). APEX consists of 12 components: climate, hydrology, crop growth, pesticide fate, nutrient cycling, erosion-sedimentation, carbon cycling, management practices, soil temperature, plant environment control, economic budgets, and subarea/routing (P. Gassman & Williams, 2009). This model is especially suited for estimating environmental impacts from animal agriculture due to waste management methods such as manure stockpiling and waste storage ponds (P. Gassman & Williams, 2009).

The Aqueduct (GLDAS) framework provides water risk estimates within three categories: 1) physical risks (quantity), 2) physical risks (quality), and 3) reputational and regulatory risks (Reig, Shiao, & Gassert, 2013). The method outputs a composite score for the water risk in a specific area, as well as individual scores for each category. This tool is ideally suited for companies seeking to expand or move operations to a different geographical location, helping identify potential water-related risks. However, this tool is limited in its application due to the complexity of information encapsulated in the single number score (Reig et al., 2013).

The Variable Monthly Flow (VMF) method is a parametric method which assesses ecosystem water demand to reach "fair ecological status" (Pastor et al., 2014). The model adjusts the region's natural environmental freshwater flow requirements (Poff et al., 2010) on a monthly basis according to flow season, providing a reserve of 60% of maximum monthly flows (MMF) during low-flow seasons, leaving 40% for other users, and 30% of MMF during high-flow seasons

(Pastor et al., 2014). Low-flow and high-flow seasons are determined when the MMF is below or above the mean annual flow (MAF), respectively (Pastor et al., 2014).

2.7 Crop Models

CROPWAT estimates crop water requirements based on crop data, soil composition, and climate. It can be useful in estimating crop performance under varying conditions, such as irrigation or rain-fed conditions. Calculations are based on two categories: 1) crop evapotranspiration and 2) crop yield response to water. This methodology is used in hydrological models like WaterGAP to estimate agricultural water use.

The Earthstat database provides global distribution information about 175 crops on a global scale. It combines the use of subnational crop statistical surveys with remote sensing technologies identifying crop land cover (Monfreda, Ramankutty, & Foley, 2008). Combining these two information sources allows development of agricultural land cover maps (Monfreda et al., 2008), helping identify the geographic distribution and intensity of crops grown on a global scale.

MIRCA2000 is a dataset of irrigated and rain-fed crop areas on a global scale. Using remote sensing at a 5-arc minute resolution, MIRCA2000 provides monthly crop areas of 26 crop classes, including all major food crops. Data is based on the year 2000.

2.8 Primary Data Sources

Various U.S. and international agencies generate and distribute comprehensive data which can be used for calibration and validation for water assessment methodologies. These sources, coupled with hydrological and crop models, allow calculation of water balances within basins (See Figure 8). A list of sources providing U.S. water and crop data and their possible applications and limitations are presented here.

The Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group located at Oregon State University develops spatial climate datasets to reveal short- and long-term climate patterns covering the period 1895 to present. It includes parameters for snowfall, temperature, growing degree-days, and other weather aspects (Daly, Taylor, & Gibson, 1997) . It uses point data, a digital elevation model, and event-based climactic parameters to conduct its climate analysis (Daly et al., 1997).

The United States Department of Agriculture (USDA) generates data in multiple categories. The USDA Natural Resources Conservation Service (NRCS) manages the Soil

Climate Analysis Network (SCAN) which provides soil climate monitoring from over 200 automated collection sites throughout the U.S. Monitors measure a range of elements including air and soil temperature, barometric pressure, precipitation, snow depth and water content, solar radiation, wind speed and direction, and relative humidity. NRCS also provides the Snow Telemetry (SNOTEL) data source which provides real-time and historical precipitation, snowpack, reservoir and forecast data for over 800 site monitors across 12 states. The USDA Geospatial Data Gateway provides a collection of precipitation and stream flow data from small agricultural watersheds in the United States, but is limited to 25 states.

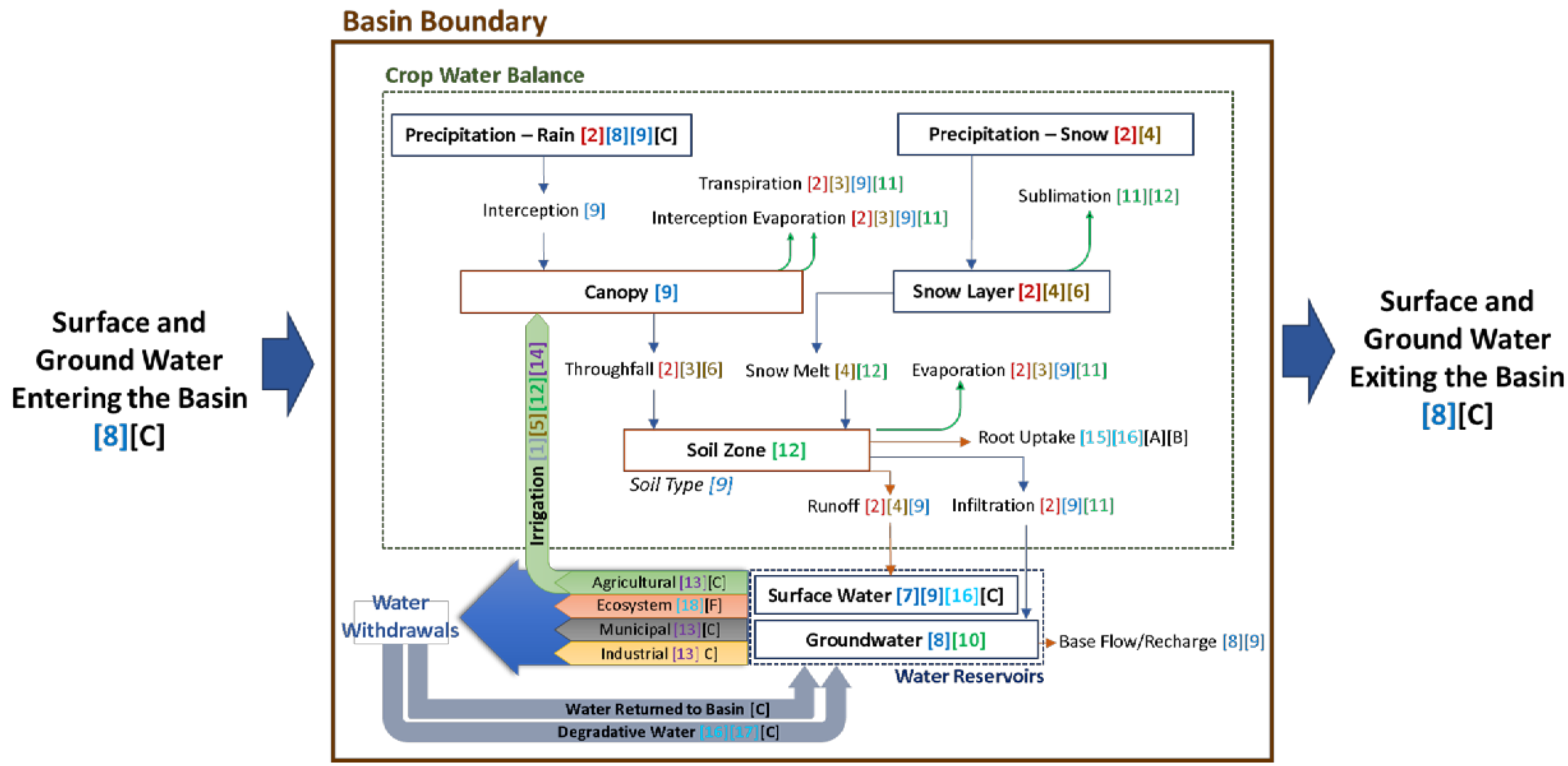
USDA Quickstat provides U.S. agricultural data published by National Agricultural Statistics Service (NASS) allowing aggregation and compilation of commodity information including production quantities, acres harvested, economic information, yield values, irrigated water use, and others. This comprehensive statistics service provides both census and survey data, and serves as a key element in the methodology later discussed in this thesis.

The Farm and Ranch Irrigation Survey is part of the census of agriculture provided by the USDA every five years, which counts U.S. farms and ranches across the U.S. The survey examines land use, ownership, production practices, and financials. The survey covers a wide range of livestock and crop types and their associated water use at both the state and county level.

The Moderate Resolution Imaging Spectroradiometer (MODIS) Toolbox provides world climate data at a 1km x 1km resolution with records starting in the year 2000. Two NASA satellites capture daily global data including evapotranspiration, land surface temperature, vegetation and land-surface cover, and others. The MODIS Toolbox, though providing data at a lower spatial resolution than other sources, serves as another data source for incorporation into existing models, or can serve as a validation tool for assessing model results.

The Global Data Runoff Center (GRDC) maintains river discharge data with global coverage (Fekete, Vörösmarty, & Grabs, 2002). With river discharge being a key factor for modeling terrestrial water cycles (Fekete et al., 2002), data from GRDC serves as an input or calibration parameter for more comprehensive hydrologic models such as WaterGAP (Joseph Alcamo et al., 2003).

The United States Geological Survey (USGS) also provides multiple data products relating to climate and water. First, the National Hydrography Dataset (NHD) and Watershed Boundary Dataset (WBD) provide surface water and drainage network information. These datasets are primarily used in GIS analysis and modeling. The USGS Water Data Discovery is a compressive resource providing current and historical water data reports on streamflow,



Primary Data Sources
[1] Farm and Ranch Irrigation Survey
[2] PRISM
[3] USDA SCAN
[4] USDA SNOTEL
[5] USDA QuickStat
[6] USDA Geospatial Gateway
[7] USGS NHD
[8] USGS Water Data Discovery
[9] USGS Geospatial Gateway
[10] NASA GRACE
[11] NASA MODIS Toolbox
[12] NSIDC SNODAS
[13] FAO AQUASTAT
[14] FAO FAOSTAT
[15] Pfister et al. 2014
[16] Hoekstra et al. 2009 (WFN)
[17] Boulay et al. 2011
[18] Mila I Canals

Crop and Hydrological Models
[A] SWAT
[B] CROPWAT
[C] WaterGAP
[D] Earthstat
[E] MIRCA2000
[F] Variable Flow Method

Additional Relevant Data: Crop Distribution (Geographically) [D][E]
Total Regional Crop Production [5][14]

Figure 8: Basin hydrological processes and water withdrawals with available models and primary data sources for each flow within the basin.

flooding, drought, groundwater levels, surface water quality, and water use. It is part of the National Water Information System (NWIS) which serves as the nation's principal repository of water resources data acquired from over 1.5 million sites nationwide.

The Food and Agriculture Organization (FAO) provides multiple data sets valuable for water use assessment in agriculture. First, AQUASTAT offers data, metadata, reports, country profiles, river basin profiles, regional analyses, maps, tables, spatial data, guidelines, and other tools on the following topics:

- Water resources: internal, transboundary, and total
- Water uses: by sector, by source, and wastewater
- Irrigation: location, area, typology, technology, and crops
- Water-related institutions, policies and legislation

FAO also provides FAOSTAT, which serves as a premier data hub for global data regarding crop and livestock production, inputs, trade, food balances, and more. FAOSTAT sources country-level agriculture data across the globe, providing a central location for global data access for food commodities.

The National Aeronautics and Space Administration (NASA) launched the Gravity Recovery and Collection Experiment (GRACE) in 2002, consisting of two satellites which measure time variation of earth's gravity field. This data, along with advanced astrophysics methods, can be used to estimate terrestrial water storage (TWS) (both surface and groundwater) (Houborg, Rodell, Li, Reichle, & Zaitchik, 2012; Wahr, Molenaar, & Bryan, 1998). This is possible due to subtle shifts in Earth's gravity which occur primarily due to water moving from one place to another on and under land, in the ocean, and in the atmosphere. Measurements of location, force, and orbital change translate into an observation of gravity. These measurements can provide a value for terrestrial water storage (TWS) at the 1^{o} and 0.5^{o} resolution. This data can be further refined to provide data specifically for surface water, soil moisture, and groundwater quantities, with data available at monthly time steps. More on the potential application of this data will be covered in the discussion section of this thesis.

3. Methods

This research aims to develop regional water stress values at the watershed level for different crop types, allowing aggregation to the state and national level for use in individual diet analysis. Additionally, import and export data for individual crops is captured and assessed to improve the water footprint accuracy for food products consumed in the United States. Based on methods and data limitations identified in the literature review, this research seeks to fill data gaps and provide a technique for regional water use impact assessment of agricultural crop production.

The methods applied in this study combine empirical data and theoretical models. As noted above, shortcomings in inventory data descriptions (i.e. source of water, quality discharged, location of withdrawal, etc.) serve as a primary gap in many water use models which rely on theoretical crop growth and yield based on climate conditions, as well as other factors. Though useful for global assessments where gaining data granularity is particularly challenging, regional studies in developed countries (such as the United States) benefit from availability of more precise and descriptive water use data. For this reason, this methodology relies on empirical data from USDA and FAOSTAT for determining domestic production and trade quantities, respectively, for all crops assessed.

Regionally characterized water consumption at the basin and county level are aggregated to determine state and national values. Crops imported and exported are characterized differently, with Imports characterized at the national level of the country of origin, and exports characterized as a U.S. production-weighted average. More detail and explanation regarding the characterization of different trade elements occurs in following sections. Final characterized results will represent the water use in competition of various crops consumed in the U.S.

A case study to demonstrate the proposed methodology includes assessment of 10 crops: barley, oats, peanuts, potatoes, rice, rye, soybeans, sugar beets, sweet potatoes, and wheat. These crops were chosen based on their diversity of uses, differences in regional production, and availability of production data at the county level. Crops such as barley, oats, soybeans, and wheat represent field crops, most with significant inputs into livestock production, while peanuts, potatoes, rice, sugar beets and sweet potatoes are primarily used as direct consumption crops (some undergoing processing prior to consumption). Wheat and barley are used for a mixture of uses including livestock production and ingredients in consumer products (including alcohol).

3.1 Regional Characterization Factors

AWARE characterization factors (Anne-Marie Boulay et al., 2016) were used to characterize regional water competition. AWARE was chosen for many reasons, one being use of WaterGAP, which serves as the most comprehensive global hydrological model available by including anthropogenic water withdrawals and water quality assessment. Additionally, the AWARE model incorporates regional ecological water requirements using the VMF method, adding to its comprehensive assessment of regional water requirements. Finally, the AWARE methodology has received wide acceptance among LCA practitioners and is anticipated to become the standard for assessing water footprints of products, processes and services. For these reasons, AWARE is the most appropriate method for characterizing impacts in this case study.

State and county boundary lines were consolidated using cartographic boundary shapefiles from the U.S. Census Bureau (U.S. DoC, 2016), with each county having a unique Federal Information Processing Standards (FIPS) code for assigning, summing and averaging water stress indicators to each county. Using GIS software, this data was projected from geographic (decimal degrees) to USA Contiguous Albers Equal Area Conic to ensure conformity among data sets. A KML file for the polygons was used to join the county shapefile to a document with tabulated AWARE characterization factors at 5 arc minute grid intervals to populate the water characterization attributes with the county boundary lines. Regional attributes from AWARE which were incorporated and assigned during this process include water consumption (from all sources), the average water characterization factor for each month, and the annual average irrigated water characterization factor. This layer was re-projected to match the counties layer, with the final layer being converted to a raster (grid) separately for each attribute using a 1 km x 1 km grid. Zonal statistics were used to generate a table providing attribute means for each county. Essentially, this process took an area-weighted average of the attribute values in each county. Finally, this table was joined to the county layer attribute table by FIPS code, resulting in county-level averages for each AWARE attribute.

3.2 Domestic Production Data

Crop production data was gathered from USDA NASS, with priority given to census data rather than survey data. USDA conducts a census of agriculture every five years, and data is available for the years 1997, 2002, 2007 and 2012. The census provides “the only source of uniform, comprehensive agricultural data for every county in the nation,” covering over 3000 counties in all 50 states and includes all farms and ranches selling over $1,000 of agricultural products (USDA, 2017). For incomplete or under-covered crops or areas, NASS supplements and adjusts data using reweighting techniques to achieve consistency and completeness. For these reasons, census data served as the primary source for crop production values at the county level.

Surveys could serve as a secondary source of crop production data, especially given the limited number of crops covered by each census at the county level (more data is available at the state level). Surveys are collected in smaller sample sizes with the intent to estimate production totals, thus are not as comprehensive as census data. Though less comprehensive, survey data is available at the county level and provides insight into growing regions and estimated quantities of production in each region, which are necessary components in assessing water competition footprints of U.S. consumed crops. Surveys are conducted quarterly for various crops, providing data availability for a multitude of crops not covered by census data.

All assessed crops in the following case study had readily available county-level census data for production totals. Some crops, such as soybeans, have data for each census between 1997 to 2012. Other crops were only assessed during a couple census events in that same timeframe. To account for varying time spans in recorded data, production values for each county were averaged for all census data available for each crop.

Some census data are not disclosed to the public to maintain anonymity for some farmers in specific counties. This missing data leads to incomplete information at the county level, and is the reason for reported crop production totals being different between county, state and national levels. With production quantities and regional contributions to total consumed crops integral elements to accurately assess water use, USDA data was compared at county, state and national level to determine discrepancies. County data were summed to generate state values and compared with USDA reported state totals, and a similar process was conducted for state totals and compared with national crop production totals. These totals and their respective differences for each crop are displayed in Table 7. Though some data is incomplete or withheld, the differences in aggregated totals of county production values and national values is less than 11% for all crops, with sweet potatoes, potatoes, peanuts and oats showing the greatest differences. Differences between aggregated state production values and national production values are negligible, with all crops having less than 1% difference.

Table 7: Aggregated U.S. Crop Production Totals (Tonnes) from County, State and National Level Statistics (Source: USDA NASS)

Crop	Aggregated County Production Total[1]	Aggregated State Production Total[1]	National Production Total	Difference (County to National)	Difference (State to National)
Barley	5,369,773	5,353,087	5,352,502	0.32%	0.01%
Peanuts	2,042,855	1,924,641	1,920,493	6.37%	0.22%
Potatoes	21,423,683	23,280,074	23,283,384	7.99%	0.01%
Rice	9,857,174	10,075,806	10,078,523	2.20%	0.03%
Soybeans	71,736,791	73,328,420	73,326,914	2.17%	0.00%
Sweet Potatoes	579,682	648,923	648,933	10.67%	0.00%
Wheat	54,645,862	54,951,403	55,012,855	0.67%	0.11%
Oats	1,522,339	1,618,682	1,617,970	5.91%	0.04%
Rye	176,636	172,856	172,555	2.36%	0.17%
Sugar beets	28,264,018	28,164,494	28,324,290	0.21%	0.56%

[1] *Crop totals are aggregated and averaged from census data from 1997, 2002, 2007 and 2012*

Crop production totals reported in bushels, including wheat, barley, rye and soybeans were converted to tonnes using conversion factors provided by the U.S. Grains Council (U.S. Grains Council, 2017). Conversion factors are provided in Table 8**.**

3.3 Irrigation Water Requirements

Multiple sources exist for estimating uncharacterized crop water requirements, each functioning under different assumptions and underlying models. Hoekstra et al. (2010) provides state-level estimated water consumption for each crop including blue, green and gray water. Pfister & Bayer (Stephan Pfister & Bayer, 2014; Stephan Pfister et al., 2011) also provide water requirements, but at the national level. The data chosen for this case study is from Pfister & Bayer (2017) which provides regional crop irrigation water consumption values (i.e. blue water), which were averaged at the county level. In a similar process to developing the county-level AWARE characterization factors, GIS shapefiles providing water demand values for 160 crops with global coverage (at 5 arc minute resolution) were averaged within county boundary lines, resulting in blue water demand values for individual crops at the county level. This data set also included green water values which were also averaged at the county level, though these values were not incorporated into the proposed methodology. This data provided by Pfister & Bayer (2017) relies on input from EarthStat for determining geospatial distribution of production regions for specific crops, and CROPWAT for assessing irrigation water consumption based on climate, soil, and other

Table 8: Conversion factors for bushels of crops (U.S. Grains Council)

Crop	Conversion Factor
Barley	45.930 Bushels / Tonne
Corn	39.368 Bushels / Tonne
Wheat, Soybeans	36.744 Bushels / Tonne

considerations. Theoretical production values generated by Pfister & Bayer (2017) were also converted to county-level production estimates, and were useful for comparison against USDA reported production values used in this case study.

3.4 Domestic Water Competition Footprint

County-level AWARE characterization factors were combined with blue water irrigation requirements, resulting in a county-level characterized water competition footprint (WCF) for each crop. Additionally, using county-level crop production quantities, total blue water withdrawals for each crop were calculated. The WCF value was then combined with the county-to-national production ratio, with the sum of all footprints resulting in the crop domestic production-weighted water competition footprint ($WCF_{dom,i}$). These values were also production weighted at the state level to provide an additional spatial scale for further analysis of each crop.

$$WCF_{i,j} = CF_j \times Irrigation_{i,j}$$

$$WCF_{dom,i} = \sum_{1}^{n} \underbrace{\left(\frac{Production_{i,j}}{Production_{i,Total}}\right)}_{\substack{county-to-national \\ production\ ratio}} \times WCF_{i,j}$$

$WCF_{i,j}$ = Water competition footprint for crop i in county j (m^3 in competition/tonne)
$WCF_{dom,i}$ = Domestic production-weighted water competition footprint for crop i (m^3 in competition/tonne)
$Irrigation_{i,j}$ = Irrigation water requirement for crop i in county j (m^3/tonne)
CF_j = Characterization Factor for County j (unitless)
$Production_{i,j}$ = Production quantity of crop i in county j (tonnes)
$Production_{i,Total}$ = Total national production of crop i (tonnes)
n = number of counties reporting data for crop i

3.5 Trade Considerations

Crop import data was accessed through FAOSTAT, which provides monthly import data including countries of origin and quantities. Similarly, export data was accessed through FAOSTAT providing export quantities for each crop and destination countries. Imports and exports require special consideration, however, when determining consumed crop water use impacts at the national level. Specifically, crop imports pose certain challenges given differentiation between crops imported and consumed and those imported and immediately exported (Figure 9), an occurrence which is not well documented in available statistical databases. Without knowing the magnitude of these “pass through” effects, this methodology assumes all imports are combined with domestically produced crops for consumption. Export values are characterized the same as the U.S. domestic production-weighted national average, representing that the U.S. only exports crops which it produces domestically (i.e. no "pass through" effect).

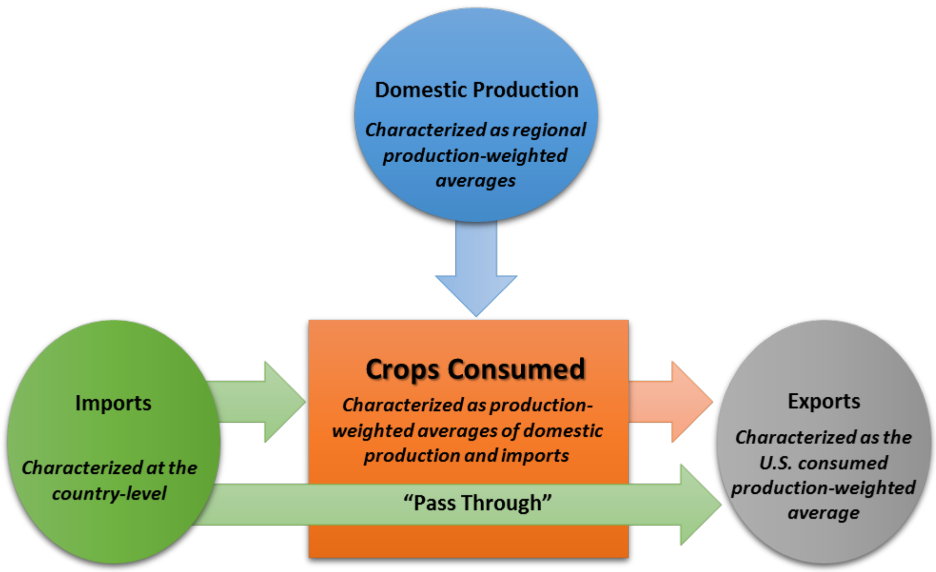


Figure 9: Characterization of imports and exports to determine production-weighted average characterization for U.S. consumed crops.

$$Consumption_{i,Total} = \left(Production_{i,Total} - Export_{i,Total}\right) + Import_{i,Total}$$

Where $Consumption_{i,Total}$ is the U.S. consumption quantity of crop *i*, $Production_{i,Total}$ is the U.S. production quantity of crop *i*, $Imports_{i,Total}$ is the total import quantity of crop *i*, and $Exports_{i,Total}$ is the total export quantity of crop *i*. As described in a later section, domestic water irrigation values are characterized at the watershed and county level, while imports are characterized at the national level based on the country of origin. Export values are characterized by the U.S. domestic production-weighted average (which only includes domestic production).

Though domestic crops are characterized at the county level, comprehensive geospatial distribution and production data for import crops is not readily available. For this reason, import crops are characterized using national-level AWARE irrigation characterization factors for the importing country (Anne-Marie Boulay & Pfister, 2017). In future studies, use of EarthStat coupled with empirical data from FAOSTAT and individual country statistics could provide additional accuracy in the characterization of imported crops. Crop irrigation requirements for import countries were taken from Pfister & Bayer (2014). National-level irrigation requirements were used for the same reasons stated above.

In a similar process to the domestic water competition footprint calculations, import crop water competition footprints were calculated by multiplying national-level characterization factors with irrigation requirements. Using a ratio of individual country import quantities over total imports, import-specific water competition footprints were generated for each crop.

$$WCF_{i,m} = CF_m \times Irrigation_{i,m}$$

$$WCF_{imp,i} = \sum_{1}^{n} \left(\frac{Import_{i,m}}{Import_{i,Total}} \right) \times WCF_{i,m}$$

$WCF_{i,m}$ = Water competition footprint for crop i from import country m (m^3 in competition/tonne)
$WCF_{imp,i}$ = National import water competition footprint for crop i (m^3 in competition/tonne)
$Irrigation_{i,m}$ = Irrigated water requirement for crop i from import country m (m^3/tonne)
CF_j = Characterization Factor for import country m (unitless)
$Import_{i,m}$ = Import quantity of crop i from import country m (tonnes)
$Import_{i,Total}$ = Total import quantity of crop i (tonnes)

Exports require no characterization or water use values. Quantities of crop exports and destination countries were accessed through FAOSTAT in a similar process the import steps outlined above. With the assumption that the U.S. only exports U.S.-produced crops (vice permitting "pass through" of imports), these export quantities were subtracted from total domestic production during the final characterization of U.S. consumed crops. In essence, exports reduce the characterization weight of U.S. produced crops and, in turn, increase the weight of import crop characterization.

Final calculation of the consumption water competition footprint ($WCF_{cons,i}$) for each crop involves properly weighting previously calculated water competition footprints (domestic and imports) with consumption totals using the *$Consumption_{i,Total}$* equation.

$$WCF_{cons,i} = \left(\frac{(Production_{i,Total} - Export_{i,Total})}{Consumption_{i,Total}} \right) \times WCF_{dom,i} + \left(\frac{(Import_{i,Total})}{Consumption_{i,Total}} \right) \times WCF_{imp,i}$$

$WCF_{cons,i}$ = Consumption water competition footprint for crop i (m^3 in competition / tonne)

With available data, the above method is reasonably accurate for many crop types consumed in the United States. However, certain inaccuracies arise when calculating $WCF_{cons,i}$ values for exotic crops or, more specifically, consumed crops arriving primarily through imports with limited domestic production. The above methodology relies on national-level characterization factors and irrigated water requirements when calculating water competition footprints for imported crops, which is less thorough than characterizing water use at the watershed- or basin-level (which is possible for domestic crops). National-level characterization factors fail to capture unique regional water scarcity conditions of certain growing regions, and national-level irrigated water requirements are estimated averages considering a wide range of climate and environmental conditions throughout a country. Due to these factors, water competition footprints for crops supplied primarily through imports may be less accurate than crops with primarily domestic production. These shortcomings emphasize this methodology as applicable to crops primarily produced and consumed in the U.S.

4. Results and Case Study

4.1 Regional Characterization Factors

AWARE factors generated at the county level (Figure 10) reveal the greatest water deprivation occurring primarily in the western and southwestern United States, areas typically associated with arid climate conditions. Over 57% of U.S. counties have characterization factors greater than 1, identifying them as having water deprivation greater than the world average. Also, Figure 10 shows the impact anthropogenic water use has on regional water deprivation, most notably in southern California near San Diego and Los Angeles, along the east coast, and even the island of Oahu in Hawaii. State-level characterization (Figure 11) shows Arizona has the highest average water deprivation (96.73), while the lowest deprivation is in Alaska (0.25).

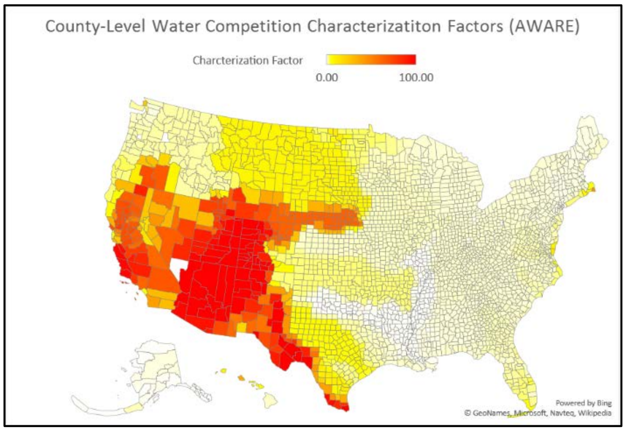


Figure 10: AWARE Characterization Factors at county-level

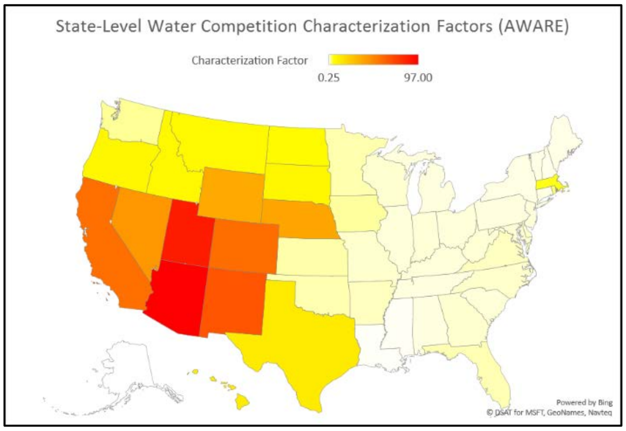


Figure 11: AWARE Characterization factors at state-level

Mapping regional crop production densities for each crop (See Appendix A) reveals concentrated pockets of activity, with each crop having unique production regions. Field crops, many of which serve as feed for livestock, have significant production density in the Midwest, having modest levels of production in other areas. Wheat and barley are nearly identical in their production regions primarily in the Northern and Western U.S., having minimal production in the southeast. Specialty crops including rice, sugar beets and peanuts, have limited production regions.

4.2 Regional Irrigation Requirements and Competition Footprints

Table 9 provides a comparative summary of state-level irrigation water requirements and water competition footprints for each crop, which reflect the change associated with characterizing water use at regional levels. Competition footprint units are in m^3-eq per tonne, which is represented more explicitly in units of m^3 in competition per tonne. California, Arizona, New Mexico, and Nebraska claim the highest production-weighted water competition footprint (WCF_{pw}) for each crop. Arizona has the highest WCF_{pw} for three crops including potatoes, barley and wheat. Arizona also has the highest overall water scarcity characterization factor, which undoubtedly contributes to high WCF_{pw} values. In contrast, states situated among the Great Lakes region and along the eastern seaboard have the lowest WCF_{pw} values. This is due to more abundant freshwater supplies, but is also attributable to the lesser production quantities of certain crops originating from these regions, which lessens their impact in comparison to other high-production states.

Below is a case study showing specific results for U.S.-grown peanuts. Results for the other nine crops can be found in Appendix A.

4.3 Case Study: Regional and National Competition Footprints of U.S. Peanuts

Peanuts are primarily produced in Georgia, Texas, Alabama and Florida, with each state contributing 41%, 16%, 12% and 9% to total domestic production, respectively. Adding irrigation requirements reveals less contribution to irrigated water withdrawals from states in the southeast (primarily Georgia, Alabama, and Florida) and increased water intensity in Texas and New Mexico. Further, after applying characterization factors based on regional water scarcity, water competition is primarily visible in Texas (56% contribution to the national WCF_{pw}) and New Mexico (20%), with other states contributing an aggregated total 25% to the national WCF_{pw}. Though New Mexico only produces approximately 1% of U.S. peanuts, it provides 20% of the crop's total water competition footprint. The irrigated water requirement for domestically grown peanuts is 273 m^3 / tonne, and the consumed WCF_{pw} is 1,264 m^3-eq / tonne.

U.S. peanuts are produced in the South-Eastern U.S. and throughout the Texas and Oklahoma region (Figure 12). Irrigation requirements are highest in the same regions, with lesser quantities of irrigation required in Georgia and other east coast states compared to Texas and New Mexico (Figure 13). Once irrigation water is characterized, counties within Texas and New Mexico appear as states with domestic water competition footprints far exceeding other regions (Figure 14). As seen in Figure 15, eastern states are situated in almost linear fashion with respect to domestic WCF_{pw}, each having varying levels of irrigation requirements but similar water footprints. However, Texas and New Mexico have substantially higher WCF_{pw} values (2,880 m^3-eq/tonne and 20,812 m^3-eq/tonne, respectively), increasing the national average. Interestingly, only 1% of U.S. peanuts are produced in New Mexico, but production within this region contributes over 20% towards the crop's domestic WCF_{pw} (Figure 16). Similarly, Texas only produces 16% of U.S. peanuts but contributes over 55% to the crop's WCF_{pw}. Results indicate a benefit of sourcing peanuts from the eastern U.S. if seeking to reduce the water footprint of consumed peanuts.

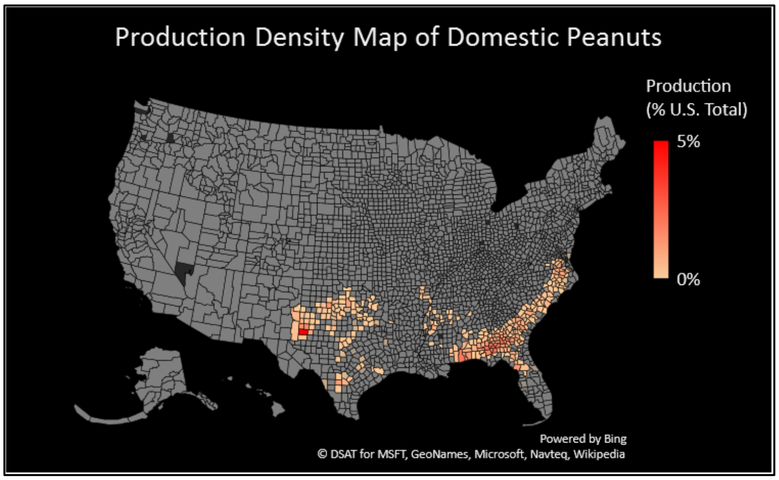


Figure 12: Production density map of U.S.-grown peanuts

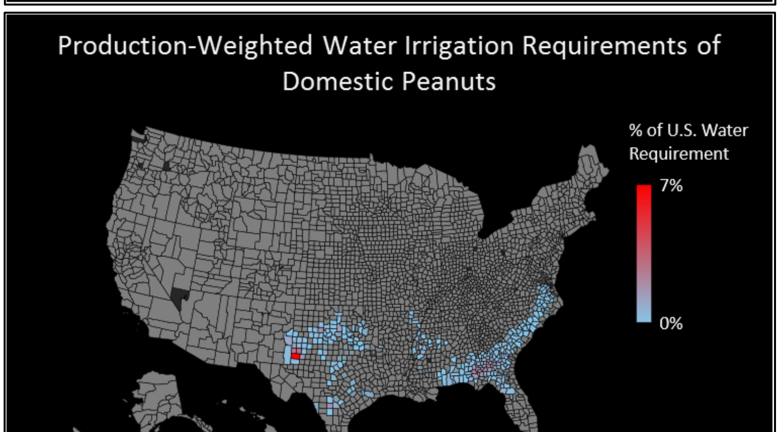


Figure 13: Irrigation water intensity map for U.S.-grown peanuts

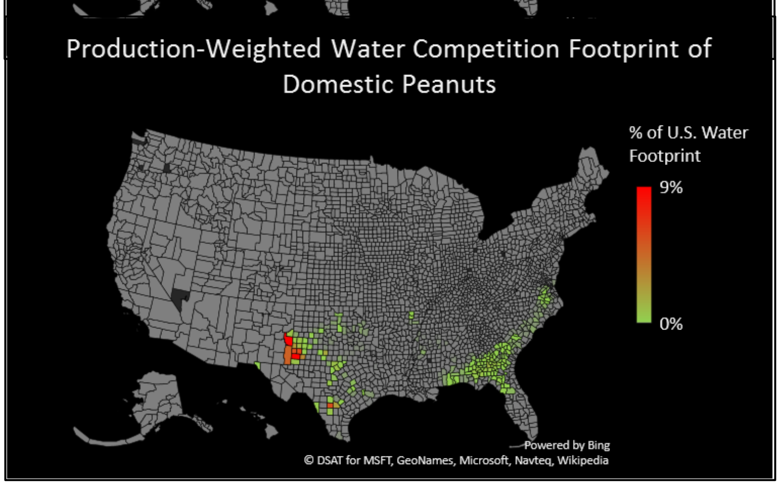


Figure 14: Water competition footprint intensity map for U.S.-grown peanuts

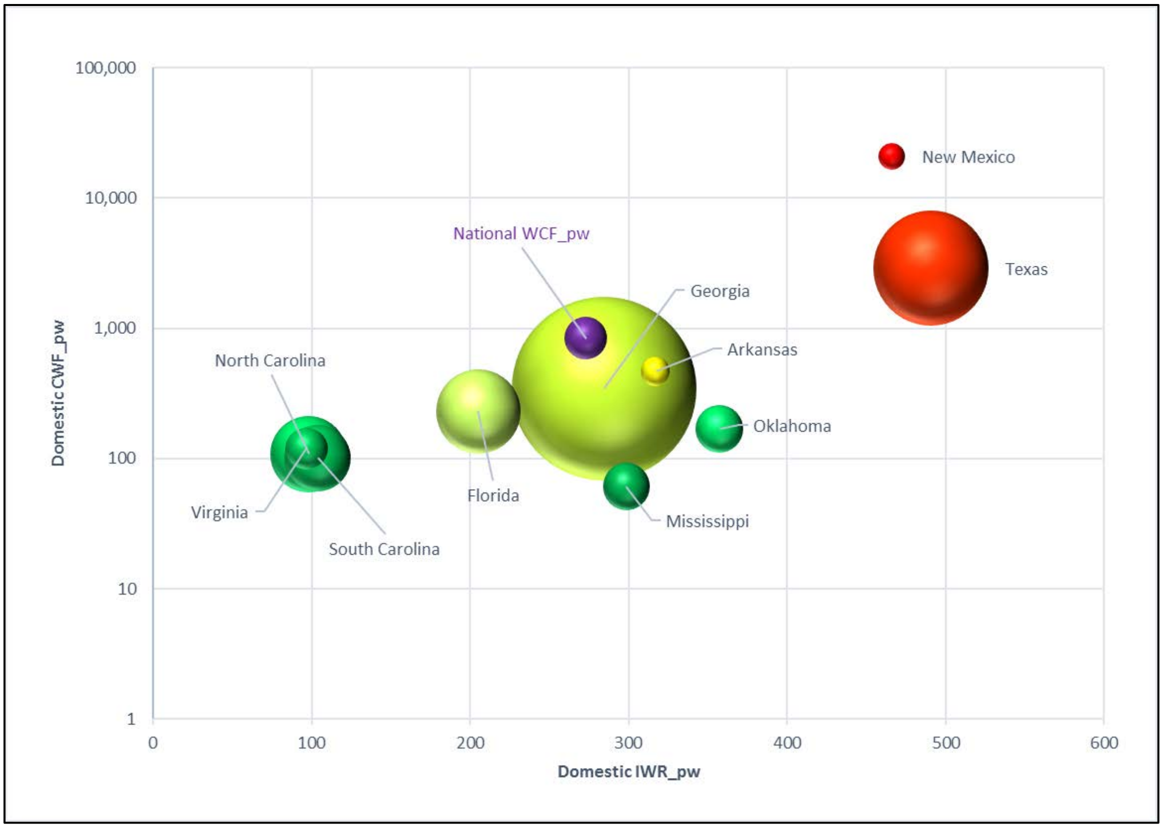


Figure 15: Bubble chart comparing peanut-producing states. Bubbles are situated based on irrigate water requirements and water competition footprints, and bubble sizes represent production quantities.

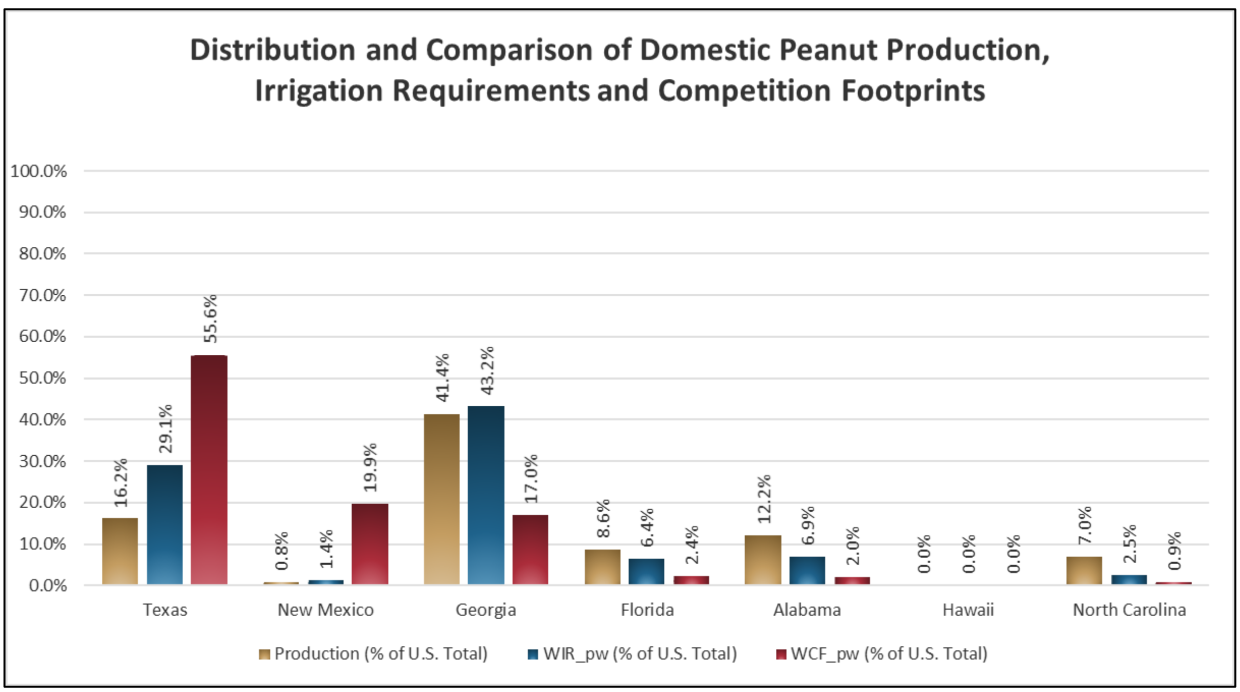


Figure 16: Distribution and Comparison of Domestic Peanut Production, Irrigation Requirements and Competition Footprints

4.4 National Competition Footprints

The national-level statistics for each crop can be found in Table 9. The differences between IWR_{pw} and WCF_{pw} for each crop and state shows the impact of water characterization, which is small in water abundant states such as Alabama and New York, but is high in arid states such as Colorado, Arizona and California. Production, import and export data provide magnitudes necessary for calculating the final consumed WCF_{pw} value (Table 10). Rice has the highest consumed WCF_{pw} among the assessed crops, with a value of 15,623 m^3-eq / tonne consumed. Sugar beets have the lowest consumed WCF_{pw} value, being 704 m^3-eq / tonne consumed. Tables 11 and 12 provide additional comparisons between key values in Table 10, showing the

Table 9: Production-Weighted Irrigation Water Requirement (IWR_{pw}) and Production-Weighted Water Competition Footprint (WCF_{pw}) aggregated at the state level. All values represent domestic production exclusively.

State	Potatoes		Barley		Peanuts		Soybeans		Sweet Potatoes		Wheat		Rice		Oats		Rye		Sugar beets	
	IWR_{pw}	WCF_{pw}	IWR_{pw}	WCF_{pw}	IWR_{pw}	WCF_{pw}	IWR_{pw}	WCF_{pw}	IWR_{pw}	WCF_{pw}	IWR_{pw}	WCF_{pw}	IWR_{pw}	WCF_{pw}	IWR_{pw}	WCF_{pw}	IWR_{pw}	WCF_{pw}	IWR_{pw}	WCF_{pw}
Alabama	11	11	6	5	156	136	164	146	13	12	46	40	0	0	224	191	570	503	0	0
Alaska	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Arizona	201	20,133	720	70,771	0	0	0	0	0	0	743	72,886	0	0	1,066	101,222	0	0	0	0
Arkansas	88	218	0	0	317	466	1,059	1,368	29	20	338	549	607	906	421	556	0	0	0	0
California	105	7,661	418	32,398	0	0	0	0	273	19,856	459	28,142	997	70,543	614	39,874	3,610	245,466	121	5,952
Colorado	126	11,887	528	47,679	0	0	541	16,362	0	0	484	18,413	0	0	857	76,728	2,186	209,509	70	3,609
Connecticut	23	15	0	0	0	0	0	0	0	0	20	19	0	0	0	0	0	0	0	0
Delaware	40	55	80	110	0	0	650	887	0	0	70	95	0	0	122	162	0	0	0	0
Florida	40	89	0	0	205	231	502	555	88	183	152	148	358	759	324	326	910	1,227	0	0
Georgia	5	6	14	15	285	344	674	805	2	3	265	308	0	0	383	451	779	957	0	0
Hawaii	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Idaho	91	286	256	1,255	0	0	0	0	0	0	222	1,284	0	0	459	2,770	0	0	86	248
Illinois	24	30	41	36	0	0	115	108	3	3	26	20	0	0	45	53	3	4	0	0
Indiana	19	19	17	17	0	0	115	114	0	0	15	15	0	0	26	25	2	2	0	0
Iowa	27	33	86	236	0	0	159	456	0	0	103	186	0	0	72	174	19	55	0	0
Kansas	89	237	269	524	0	0	617	1,325	0	0	348	720	0	0	261	512	122	298	0	0
Kentucky	14	11	12	11	0	0	263	116	13	12	31	14	0	0	18	16	0	0	0	0
Louisiana	51	8	0	0	0	0	897	190	79	13	592	106	356	179	436	65	0	0	0	0
Maine	13	7	6	3	0	0	214	119	0	0	5	3	0	0	7	4	0	0	0	0
Maryland	40	39	53	55	0	0	435	500	0	1	52	57	0	0	26	30	0	1	0	0
Massachusetts	29	18	1	1	0	0	371	229	0	0	0	0	0	0	30	15	0	0	0	0
Michigan	26	23	25	22	0	0	172	148	0	0	19	17	0	0	37	31	1	1	5	4
Minnesota	21	36	36	101	0	0	127	267	0	0	48	138	0	0	57	113	4	8	6	15
Mississippi	6	1	0	0	299	61	903	151	74	15	510	79	542	79	189	76	0	0	0	0
Missouri	69	12	178	264	0	0	429	308	0	0	192	221	634	250	160	217	80	92	0	0
Montana	54	271	179	1,438	0	0	249	2,111	0	0	151	1,256	0	0	179	1,173	28	237	46	390
Nebraska	42	523	324	13,290	0	0	667	30,934	0	0	433	17,280	0	0	319	13,533	165	8,489	61	2,570
Nevada	0	0	475	23,468	0	0	0	0	0	0	277	12,271	0	0	296	10,857	5	226	0	0
New Hampshire	9	5	0	0	0	0	118	63	0	0	0	0	0	0	10	7	0	0	0	0
New Jersey	37	64	51	71	0	0	542	711	128	165	60	94	0	0	31	20	0	0	0	0
New Mexico	82	1,987	176	14,153	466	20,812	0	0	0	0	768	25,110	0	0	684	58,667	0	0	0	0
New York	28	42	24	20	0	0	173	145	4	7	20	17	0	0	33	28	0	0	0	0
North Carolina	9	11	65	66	98	108	268	323	34	39	98	115	0	0	154	180	82	92	0	0
North Dakota	14	67	70	469	0	0	205	995	0	0	92	643	0	0	116	865	24	199	8	41
Ohio	18	16	14	13	0	0	137	126	11	11	17	15	0	0	21	20	0	0	5	4
Oklahoma	83	91	428	237	357	169	1,067	2,421	0	0	476	761	0	0	424	720	238	261	0	0
Oregon	88	319	240	1,728	0	0	0	0	0	0	209	506	0	0	357	3,061	562	4,951	82	613
Pennsylvania	16	14	22	19	0	0	218	180	9	8	27	22	0	0	21	18	0	0	0	0
Rhode Island	5	42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
South Carolina	17	17	47	42	104	101	326	313	6	7	138	132	0	0	235	238	280	279	0	0
South Dakota	37	314	172	1,430	0	0	243	2,002	0	0	148	1,237	0	0	139	1,165	27	219	0	0
Tennessee	12	11	11	11	115	113	754	118	13	12	75	12	637	64	21	16	0	0	0	0
Texas	83	2,248	238	810	491	2,880	932	5,376	1	2	643	2,793	219	1,008	586	4,511	1,258	6,388	0	0
Utah	83	7,549	390	32,020	0	0	0	0	0	0	396	31,963	0	0	887	79,133	0	0	0	0
Vermont	27	20	23	19	0	0	188	158	0	0	22	19	0	0	35	26	1	0	5	4
Virginia	25	295	45	121	97	119	373	1,314	42	356	54	196	0	0	78	99	1	1	0	0
Washington	89	153	254	441	0	0	0	0	0	0	217	376	0	0	452	777	0	0	87	152
West Virginia	11	11	22	29	0	0	156	190	13	13	23	29	0	0	20	22	1	1	0	0
Wisconsin	26	28	49	57	0	0	120	135	0	0	32	35	0	0	46	52	3	4	0	0
Wyoming	51	1,042	234	6,320	0	0	0	0	0	0	595	35,537	0	0	269	10,804	0	0	51	1,095

magnitude of changes between domestic IWR_{pw} and WCF_{pw} values (Table 11), as well as domestic WCF_{pw} and consumed WCF_{pw} values (Table 12). Increases between irrigation water requirements and water competition footprints range from 207% (peanuts) to 3905% (sweet potatoes).

Sweet potatoes have the highest overall competition footprint related to its irrigation water requirements, with peanuts having the lowest (Figure 17). This is due to sweet potato production occurring in California (18% of national production), which contributes 99% of total water competition impacts for the crop. Peanuts are primarily produced in the South-East U.S. where water competition is low, resulting in a low overall WCF_{pw} compared to other crops. Figure 17 displays the strong influence crop production in water scarce regions has on overall competition footprints. The five crops (sugar beets, potatoes, sweet potatoes, oats, barley) with the lowest irrigation requirements have the highest relative water competition footprints, demonstrating the larger influence growing region has on water impacts over quantities of irrigation water.

Table 12 shows the impact that imports and exports have on final consumed WCF_{pw} values, resulting in both increases and decreases among the crops assessed. Rye and oats had the most substantial decreases between domestic and consumed WCF_{pw} (54% and 44%, respectively) due to their large import quantities from countries with low competition footprints relative to U.S. production regions. For oats and rye, imports contribute towards 52% and 55% of U.S. consumption of each crop, respectively (Figure 18). Domestic production for both crops is primarily in California, Nebraska and Colorado, each with water characterization factors of 56.9, 57.6 and 37.2, respectively. Contrasting these water scarce domestic production regions with countries providing imports, we see that 85% of imported oats originate in Canada (national CF = 10), and imported rye originates in Canada (27% of imports, national CF = 10), Denmark (24% of imports, national CF = 3.3), Germany (25% of imports, national CF = 1.6) and Sweden (20% if imports, national CF = 4.6). Peanuts had very low quantities of imports but, due to the significant water scarcity in regions providing imported peanuts (Argentina imports 70% of peanuts, CF = 54), the resulting consumed WCF_{pw} value is 9% larger than domestic WCF_{pw}.

Table 10: Summary of crop production, imports, exports, production-weighted irrigation requirements (IWRpw) and production-weighted water competition footprints (WCFpw). m3-eq / tonne is equivalent to m3 in competition per tonne.

Crop	Domestic Production (tonnes)	Imports (tonnes)	Exports (tonnes)	Total Consumed (tonnes)	Domestic PWIWR (m^3/ tonne)	Domestic PWWCF (m^3-eq / tonne)	Imports PWWCF (m^3-eq / tonne)	Consumed PWWCF (m^3-eq / tonne)
Barley	5,369,773	341,415	299,612	5,411,576	185	4,951	643	4,679
Peanuts	2,042,855	12,255	214,254	1,840,857	273	838	12,371	914
Potatoes	21,423,683	412,755	444,201	21,392,236	74	1,390	274	1,368
Rice	9,857,174	603,280	3,479,785	6,980,669	634	16,366	7,773	15,623
Soybeans	71,736,791	857,321	40,482,266	32,111,846	294	2,457	3,915	2,496
Sweet Potatoes	579,682	11,964	109,970	481,676	89	3,565	1,342	3,510
Wheat	54,645,862	2,647,586	30,827,635	26,465,814	252	2,934	721	2,712
Oats	1,522,339	1,586,415	34,723	3,074,031	159	3,102	484	1,751
Rye	176,636	204,674	5,775	375,534	212	1,826	25	844
Sugarbeets	28,264,018	126,328	4,482	28,385,864	36	707	36	704

Table 10: Comparisons between domestic IWR_{pw} and WCF_{pw} values.

	PWIWR (Domestic) (m3 / tonne)	PWWCF (Domestic) (m^3 in competition / tonne)	% Change
Rice	634	16,366	2480%
Soybeans	294	2,457	734%
Peanuts	273	838	207%
Wheat	252	2,934	1065%
Rye	212	1,826	761%
Barley	185	4,951	2579%
Oats	159	3,102	1857%
Sweet Potatoes	89	3,565	3905%
Potatoes	74	1,390	1785%
Sugarbeets	36	707	1867%

Table 11: Comparisons between Domestic WCF_{pw} and Consumed WCF_{pw} values.

	PWWCF (Domestic) (m3 in competition / tonne)	PWWCF (Consumed) (m3 in competition / tonne)	% Change
Barley	4,951	4,679	-5%
Peanuts	838	914	9%
Potatoes	1,390	1,368	-2%
Rice	16,366	15,623	-5%
Soybeans	2,457	2,496	2%
Sweet Potatoes	3,565	3,510	-2%
Wheat	2,934	2,712	-8%
Oats	3,102	1,751	-44%
Rye	1,826	844	-54%
Sugarbeets	707	704	0%

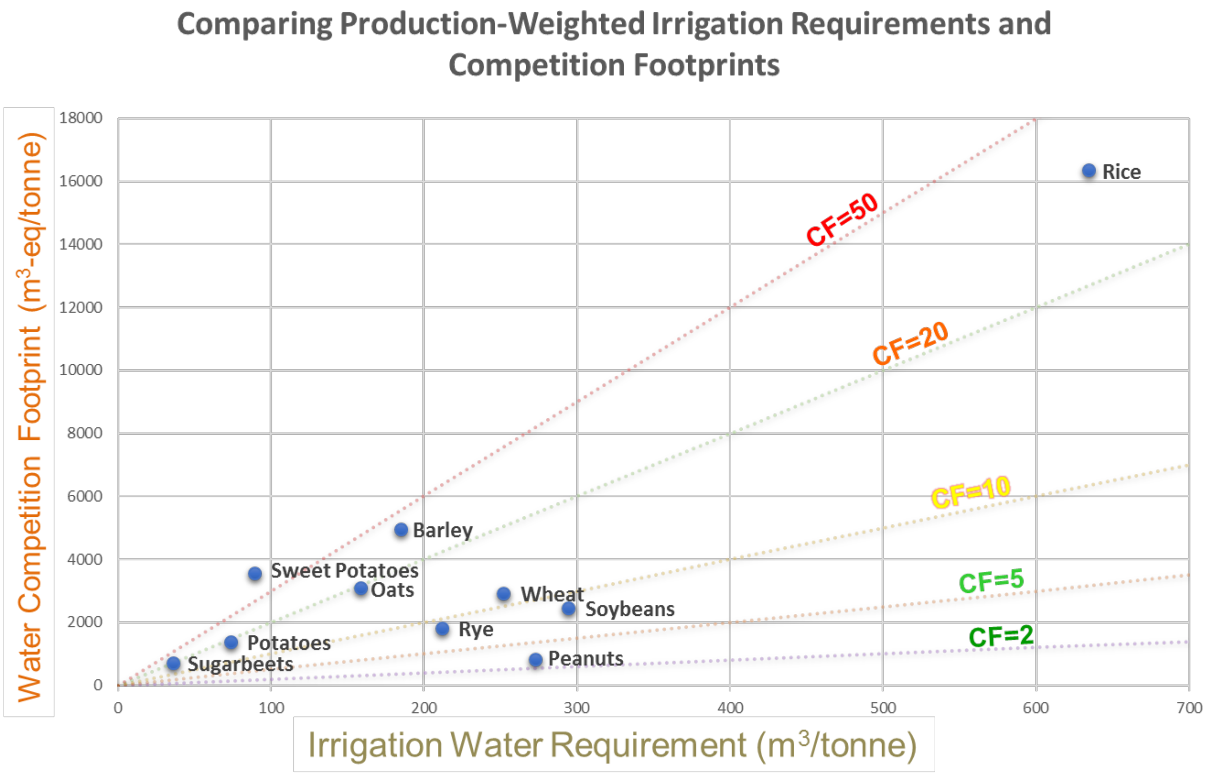


Figure 17: Chart shows bands of characterization factors from CF=2 to CF=50. Each crop marker is located at its relative domestic IWR_{pw} and WCF_{pw}, showing relative water competition associated with each crop.

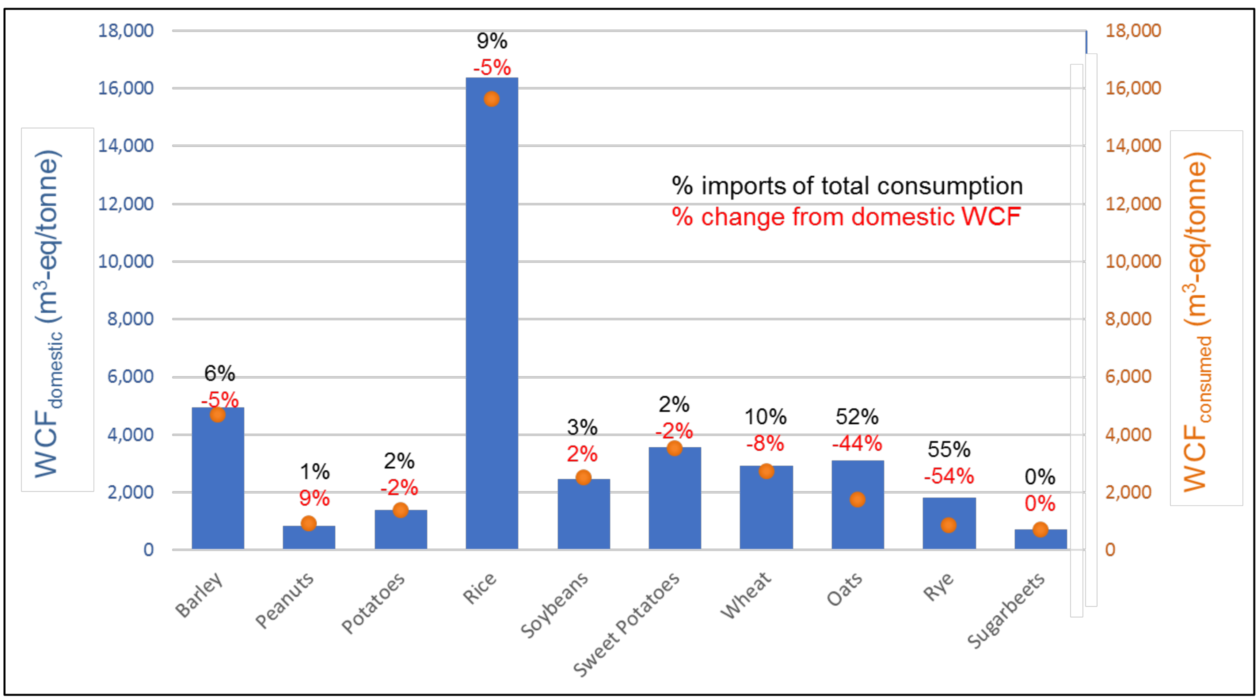


Figure 18: Influence of imports on consumed Water Competition Footprints

Certain production regions consistently provided the most contributions to irrigation water requirements and water competition footprint, most situated in the Western U.S. The states significantly contributing to high crop domestic WCF_{pw} are California, Colorado and Arizona, with those same states and Texas most contributing towards IWR_{pw} (See Table 13). Of the U.S. states most significantly contributing to IWR_{pw} and WCF_{pw} for each crop, California, Colorado, Arizona and Texas ranked among the top states. These results indicate the significant irrigation requirements and corresponding water competition occurring within these production regions.

Table 12: Three states most significantly contributing to IWR_{pw} and WCF_{pw} for each crop assessed.

Crop	Metric	States with Largest Contribution Towards Overall Impact		
Potatoes	IWR_{pw}	Arizona	Colorado	California
	WCF_{pw}	Arizona	Colorado	California
Barley	IWR_{pw}	Arizona	Colorado	Nevada
	WCF_{pw}	Arizona	Colorado	California
Peanuts	IWR_{pw}	Texas	New Mexico	Oklahoma
	WCF_{pw}	New Mexico	Texas	Arkansas
Soybeans	IWR_{pw}	Oklahoma	Arkansas	Texas
	WCF_{pw}	Nebraska	Colorado	Texas
Sweet Potatoes	IWR_{pw}	California	New Jersey	Florida
	WCF_{pw}	California	Virginia	Florida
Wheat	IWR_{pw}	New Mexico	Arizona	Texas
	WCF_{pw}	Arizona	Wyoming	Utah
Rice	IWR_{pw}	California	Tennessee	Missouri
	WCF_{pw}	California	Texas	Arkansas
Oats	IWR_{pw}	Arizona	Utah	Colorado
	WCF_{pw}	Arizona	Utah	Colorado
Rye	IWR_{pw}	California	Colorado	Texas
	WCF_{pw}	California	Colorado	Nebraska
Sugar beets	IWR_{pw}	California	Washington	Idaho
	WCF_{pw}	California	Colorado	Nebraska

5. Discussion

A major aim of this study was to determine the relationship between crop irrigation water requirements and regional water competition due to water scarcity. This is especially pertinent as irrigation water, either from surface or ground sources, is the crop water resource competing most directly with other regional users. Intuitively, increased requirement for irrigation coincides with regional water scarcity, but the strength of this relationship is not yet established. As seen in Figure 17, there is a positive relationship between IWR_{pw} and WCF_{pw}, which supports the notion that increased irrigation is, in part, correlated with regional water scarcity. Additional crop values are needed to generate a statistically significant relationship between these two indicators, but initial results show a positive trend.

Many life cycle assessment studies aimed at estimating environmental impacts of different food products are available, with most assessing greenhouse gas emissions (GHGE), land use and energy requirements (Aleksandrowicz, Green, Joy, Smith, & Haines, 2016; Clune, Crossin, & Verghese, 2017; Tom, Fischbeck, & Hendrickson, 2016). Water footprint studies for food products is a growing research area, and this thesis provides a possible methodology in identifying trade-offs between GHGE, land use, energy and water. Further, the consumption water competition footprints for crops would be useful in diet-level studies, helping determine relationships between diet healthfulness and environmental impacts. Some studies provide insight into these trade-offs (Aleksandrowicz et al., 2016; Clune et al., 2017; Tom et al., 2016), but characterized water impacts are lacking. This methodology may provide water competition footprints for different crops, allowing a more comprehensive and complete assessment of the environmental impacts of different food products.

Another useful application of this methodology would be the development of a tool to support retailers, restaurants, and consumers in determining the water competition footprint associated with the food they purchase. Consumers and businesses are becoming more aware of the environmental impacts of their purchasing decisions, and this methodology provides important information regarding the water competition associated with crops sourced from different regions. For example, a restaurant providing peanuts to customers may consider purchasing from a supplier with Georgia or South Carolina peanuts over others from Texas or New Mexico, in order to reduce the water footprint of the foods they are selling. Similar decision making is possible with all the crops assessed, and development of additional crop water competition footprints would further support informed decision making for individuals and businesses seeking to reduce their water footprint.

5.1 Method Limitations and Opportunities for Improvement

As stated in earlier sections, this methodology is most applicable for crops primarily produced domestically. The lack of regional-specific import crop production values reduces overall accuracy of the analysis in estimating national average consumption based water competition footprints. Given import countries likely have a wide spectrum of climatic conditions and growing regions, similar to the U.S., achieving increased granularity on regional production totals would increase overall robustness of the analysis. This level of detail is possible using theoretical models and mapping products including EarthStat, CROPWAT and IIASA-IFPRI (Fritz et al., 2015), and some researchers have already made progress in determining these regional values for various crops (Stephen Pfister & Bayer, 2017).

Census and survey data is limited, and future application in diet-level studies would require use of proxy values, other methods, or alternative data sources for developing a comprehensive number of crop water competition footprints. Incorporating water competition footprints into diet-level studies will require use of consumption models, many of which are based on the Food Intakes Converted to Retail Commodities Databases (FICRCD) and the Food Commodity Intake Database (FCID). FICRCD and FCID provide diet, nutrition and health information based on 354 and 65 commodities, respectively, posing a challenge when attempting to scale the proposed methodology to calculate water competition footprints for each commodity.

Some data gaps exist in using USDA production totals at the county- and state-level due to anonymity requirements of census data. Select county-level (and some state-level) production values are not provided for certain crops for this reason, leading to potential challenges when production weighting the impacts of certain crops. USDA generates production totals at the county, state and national level, each of which were used to determine the magnitude and potential impact of non-reported data. To do this, county production totals for each crop were summed within each state and compared with respective state production totals. Considering all county- and state-level comparisons for the 10 crops assessed (total of 500 comparisons between 10 crops), only 2% had differences greater than 1% between county sums and reported state totals. The greatest discrepancy was with sweet potatoes production in Louisiana, where the summed county production total was 5% different from the state production total. Similarly, state production totals were summed and compared with national crop production totals. These differences were less than 1% for each crop. Considering these results, non-reported data was not a limiting factor in the analysis of the crops presented in this thesis. However, in assessing the potential to scale this analysis to assess additional consumed crops, census data gaps for county-level production totals emerged as a limiting factor. Using annual survey data, which is less comprehensive than census data but provides an estimate of production totals based on representative samples, may resolve this limitation. Further, incorporating the EarthStat model for determining production totals and spatial distribution of production regions may make scaling this method more feasible and less cumbersome, allowing USDA data to serve as a validation tool rather than a primary data input.

Assessment of available groundwater, its recharge rates and potential for future use are considerations still not well modeled by the LCA community and, further, are not well understood by hydrologists. Specific to groundwater recharge, many methods have been proposed to model unconfined aquifer recharge rates (Arnold, Muttiah, Srinivasan, & Allen, 2000; Beigi, Tsai, & Frank, 2014; Finch, 1998; Gee & Hillel, 1988; Jie, van Heyden, Bendel, & Barthel, 2011; Kendy et al., 2003; Rushton & Ward, 1979; von Freyberg, Moeck, & Schirmer, 2015). However, all methods elicit variability in accuracy and application depending on the spatiotemporal considerations and other study-specific factors. Additionally, determining magnitude of groundwater depletion is challenging due to lack of relevant data on subsurface conditions (Konikow & Kendy, 2005).

WaterGAP, which is used for calculation of AWARE characterization factors, provides comprehensive assessment of groundwater recharge activity on a global scale. However, given the regional focus of this study, WaterGAP lacks certain components to accurately inform on regional groundwater stores and impacts. Specifically, WaterGAP does not account for groundwater flow between grid cells, treating groundwater as storage compartments without accounting for flow or recharge of surface water bodies. Without considering the complexities of aquifer topography, variable interactions with surface water bodies, and diffuse groundwater recharge (occurring through percolation due to excess soil moisture), WaterGAP does not provide the granular detail required to understand and quantify its availability for users.

Remedying this problem may come in the form of satellite-generated data from the Gravity Recovery and Climate Experiment (GRACE) mission, which provides researchers with a new source for assessing available water quantities. GRACE may provide a method for determining the magnitude of groundwater resources on a regional scale. GRACE data permits users to determine terrestrial water storage (TWS) (including snow, ice, soil moisture, surface and groundwater), and incorporation of other hydrological datasets can provide estimates of changes in groundwater storage (Famiglietti et al. 2011, Scanlon et al 2012).

More comprehensive groundwater deprivation modeling and its proper incorporation into water footprint methods is required to accurately understand the magnitude of available water within a region. Scanlon et al. (2012) calculated that between 1860 and 2007 the High Plains and

Central Valley Aquifers have decreased in available groundwater storage by 8% and 14%, respectively. Moreover, overexploitation of groundwater aquifers is a global issue, with countries including the U.S., Mexico, Iran and China both producing crops irrigated from rapidly depleting aquifers, while also importing substantial quantities of food commodities from other countries with unsustainable groundwater irrigation practices (Dalin, Wada, Kastner, & Puma, 2017). For these reasons groundwater should be modeled separately from surface-water sources using an individual groundwater footprint method. Gleeson et al. (2012) developed a method for determining groundwater footprints using aquifer area, annual abstraction, recharge rate and contributions to environmental streamflow. Regions requiring significant groundwater use for irrigation had groundwater footprints 3 to 54 times larger than the aquifer's actual area, indicating the unsustainable abstraction occurring within these agricultural regions (Gleeson et al., 2012). This requires either decoupling of groundwater considerations from the WaterGAP model or incorporation of a more robust sub-model to comprehensively capture irrigation impacts from overexploited groundwater sources.

The scope of this analysis is limited to irrigation water impacts, and does not include water impacts associated with electricity generation, fuel processes and uses, or other life cycle inputs. However, future integration of the AWARE methodology into primary databases and LCA software will enable more comprehensive water impact assessments of products, allowing practitioners to expand system boundaries to address other water intensive aspects contributing to crop production and distribution. It is likely that irrigation is the most water intensive and impactful process within a crop's life cycle, but even marginal water uses can significantly contribute to overall crop water footprints (e.g. peanuts grown in New Mexico). For this reason, future research should seek to include additional input data and characterization to accompany irrigation water requirements, allowing determination regarding how various inputs into crop systems impact cradle-to-grave water competition footprints.

6. Conclusion

This thesis sought to apply a methodology for assessing regional water impacts for crop production, and to demonstrate this approach on 10 domestic crops. After a detailed literature review, different models and primary data sources were integrated into a method for assessing crop production at the county scale. First, the AWARE method was used for determining water characterization factors within a region. These factors are a result of total water available, human consumption and ecosystem demand (Anne-Marie Boulay et al., 2016; Anne-Marie Boulay & Pfister, 2017). Second, irrigation water requirements were provided by Pfister & Bayer (2017) which include blue water irrigation water requirements with global coverage for 160 crops (Stephen Pfister & Bayer, 2017). Census data from USDA provided county-level production data for 10 different crops, and import and export quantities were accessed from FAOSTAT. Using these models and data sources, production weighted water competition footprints (WCF_{pw}) were calculated for each crop for both domestic production and consumed quantities.

Western states, most notably California, Colorado, Arizona and Texas use significant quantities of water for irrigation, and regional water scarcity imposes strong water competition among other users. Even small production quantities in the Western U.S. resulted in significant water impacts. Peanuts grown in New Mexico, for example, only account for 1% of total U.S. peanut production but contribute over 20% towards the crop's water competition footprint. Similar is the case of sweet potatoes, of which California produces only 18% of the U.S. total supply but contributes 99% towards the crop's water competition footprint. These results indicate the large water footprint and impact associated with producing crops in these regions of the Western U.S., and may be used to inform decision making about production and sourcing of crops from these regions.

High quantities of irrigation water requirements did not necessarily correspond with high water competition footprints. Peanuts, for example, had a very high irrigation water requirement (273 m^3/tonne) and the lowest overall water competition footprint (838 m^3-eq/tonne). On the other hand, sweet potatoes had one of the lowest irrigation water requirements of the crops studied (89 m^3/tonne, Table 11), but had the third highest overall water competition footprint (3,565 m^3-eq/tonne). These examples, and others, demonstrate the influence of production regions for each crop, and that irrigation water quantity is not an adequate indicator of a crop's water footprint. Additionally, these results highlight the importance of assessing water impacts at a small spatial scale (counties, in this case), focusing on watersheds rather than state or national boundaries for assessing impacts.

The proposed methodology is not without limitations, with certain primary data gaps at USDA providing challenges to accurately weighting water characterization based on county-level production quantities. Additionally, this methodology is not rapidly scalable due to heavy empirical data requirements. Use of GIS-based analysis tools and crop production models, including CROPWAT and EarthStat, may provide the opportunity to rapidly assess additional crops with more flexibility and completeness. Regarding groundwater, additional research is needed to incorporate a more robust groundwater footprint model into the existing methodology. Groundwater depletion impacts are significant and occurring globally, and future methods need to assess groundwater impacts separately from surface water sources. Additionally, identification of extraction water sources (surface water or groundwater) needs to be better modeled to allow more accurate assessment of ecosystem and competition impacts from water consumption within a region.

Water is a limited resource, and its use for crop irrigation provides a potent and widespread impact throughout regions of the U.S. The method proposed in this thesis has potential to inform U.S water policy regarding crop production practices and water allocation, and may be used to inform retailers and businesses on where to source food products with varying levels of water competition footprints. The proposed consumption water footprints may enable future life cycle assessment (LCA) studies around food products, specifically analyzing the trade-offs between GHGE, energy, land use and water. Further, opportunities exist for use in diet-level studies to establish a link between environmental impacts, water footprints and healthfulness of various diets. This work successfully integrated recent water characterization methodologies and datasets to assess water competition footprints for food production and consumption in the U.S. The approach demonstrated in this thesis serves as a foundation for future research focused on regional characterization and assessment of water use and competition impacts. This assessment is necessary to better inform policy and decision making for enhancing the sustainability of food systems.

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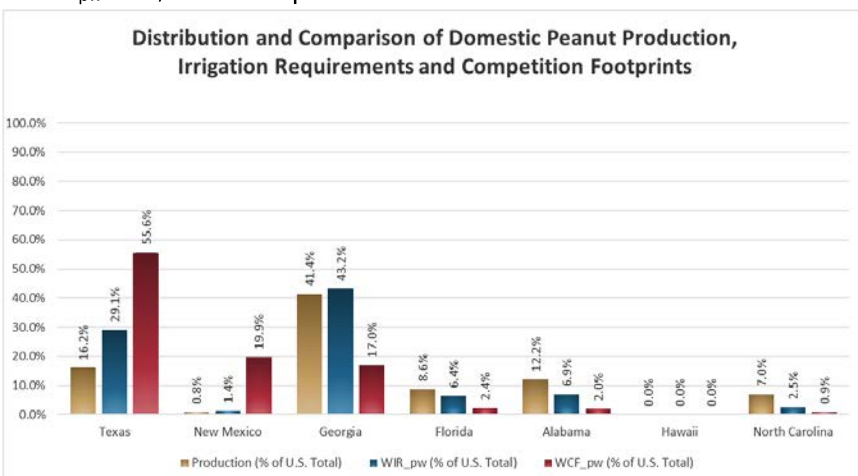
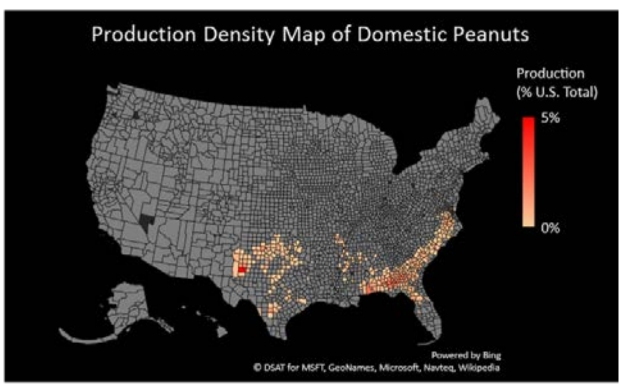
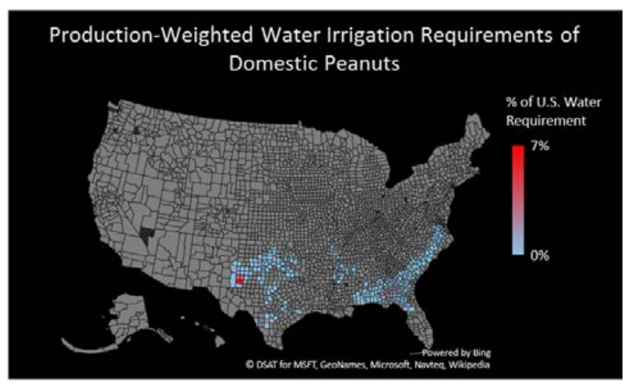
Appendix A: Individual Crop Results and Graphics

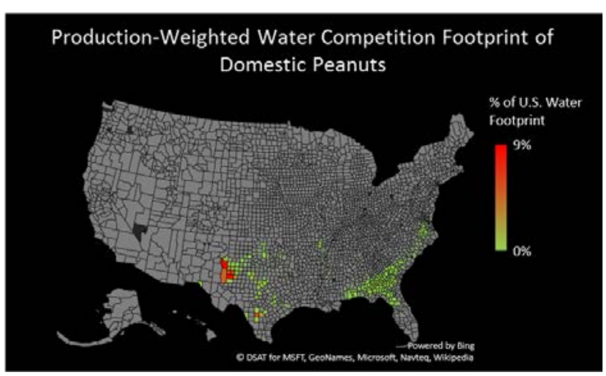
Peanuts

Peanuts are primarily produced in Georgia, Texas, Alabama and Florida, with each state contributing 41%, 16%, 12% and 9% to total domestic production, respectively. Adding irrigation requirements reveals less contribution to irrigated water withdrawals from states in the southeast (primarily Georgia, Alabama, and Florida) and increased water intensity in Texas and New Mexico. Further, after applying characterization factors based on regional water scarcity, water competition is primarily visible in Texas (56% contribution to the national WCF_{pw}) and New Mexico (20%), with other states contributing an aggregated total 25% to the national WCF_{pw}. Though New Mexico only produces approximately 1% of U.S. peanuts, it provides 20% of the crop's total water competition footprint. Domestic peanut irrigated water requirements are 273 m^3 / tonne, and consumed WCF_{pw} is 1,264 m^3-eq / tonne.



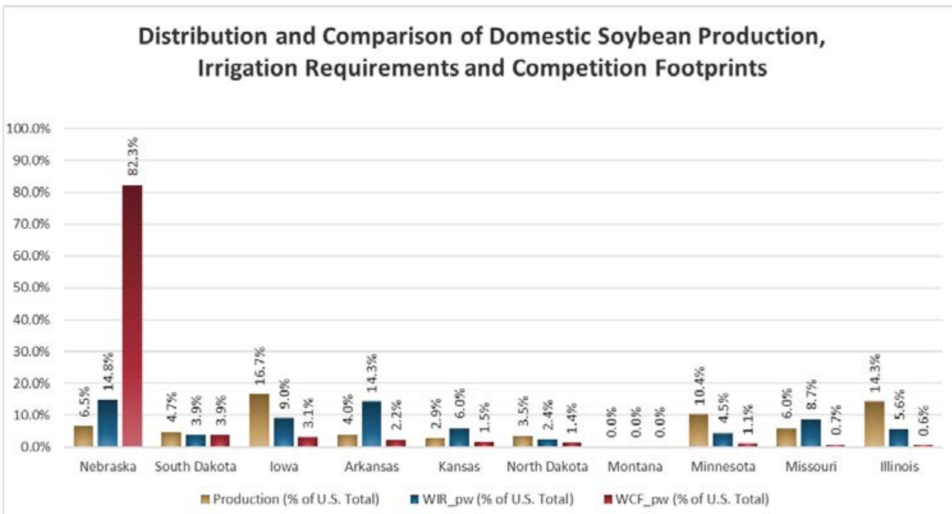


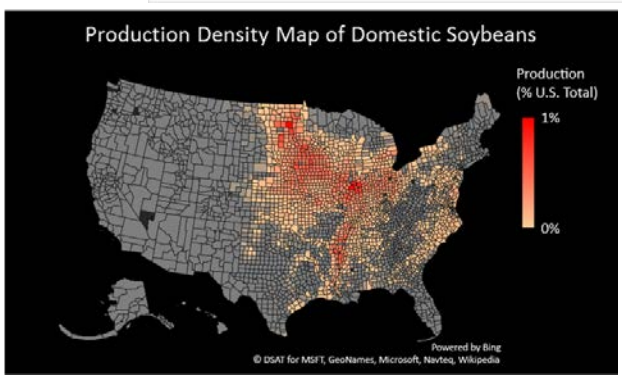


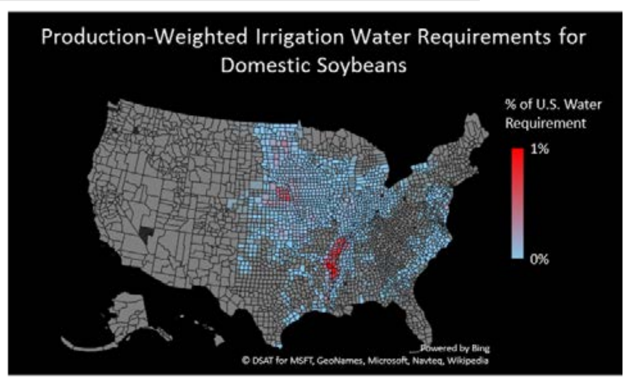


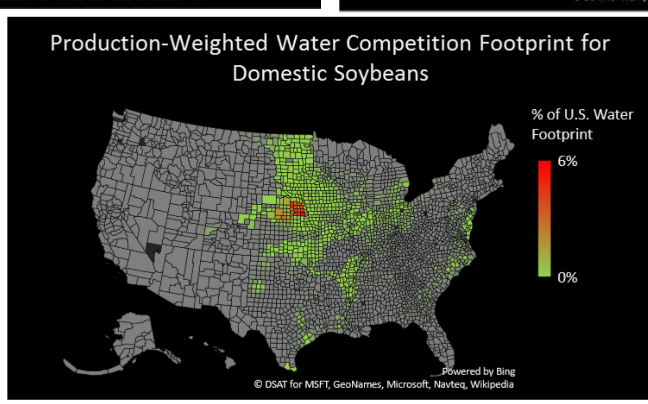
Soybeans

Soybeans are produced throughout the Mid-West U.S., with over 50% of production occurring in Iowa, Illinois, Minnesota and Indiana. Water irrigation requirements are most significant in the southern Mississippi River Basin and areas around Nebraska, but overall irrigated water withdrawals remain dispersed throughout the Mid-West. After incorporating water characterization, water competition is most noticeable in Nebraska (82% contribution to the national WCF_{pw}) and South Dakota (4%), with small pockets of water competition in Iowa (3%), Arkansas (2%) and Kansas (2%). Similar to New Mexico in the peanut results provided above, Nebraska provides a modest amount of U.S. soybean production (7%), but contributes 82% of the crop's total water competition footprint. The domestic IWR_{pw} and consumed WCF_{pw} for soybeans are 294 m^3/tonne and 2,563 m^3-eq / tonne, respectively.



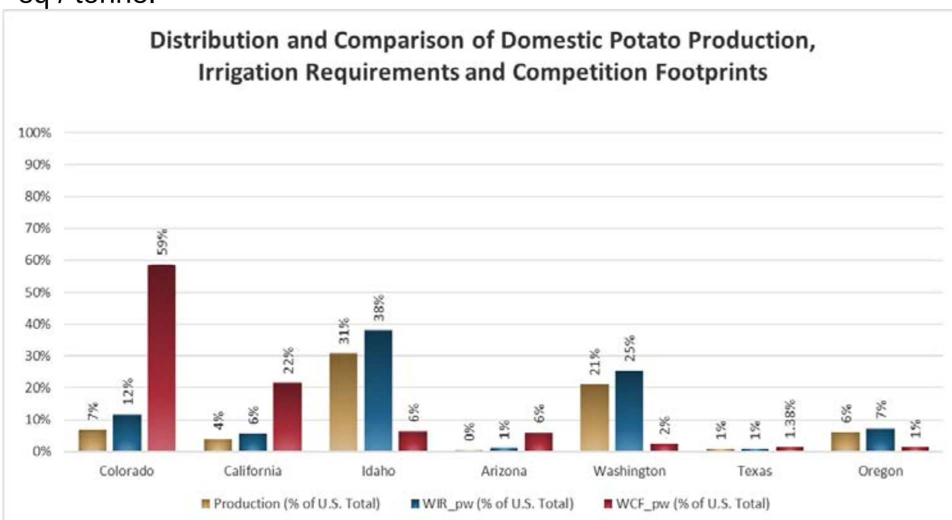


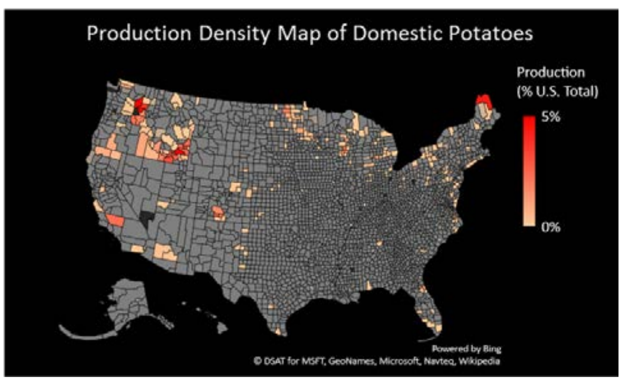


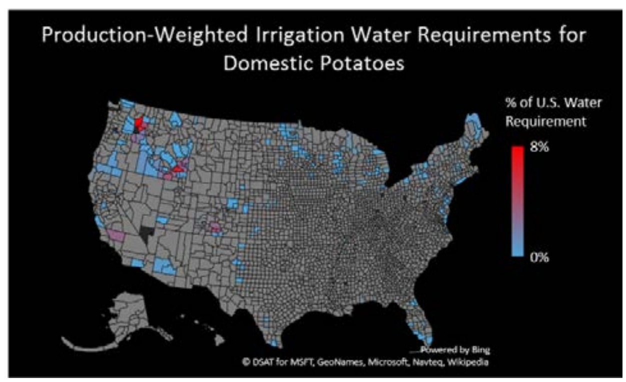


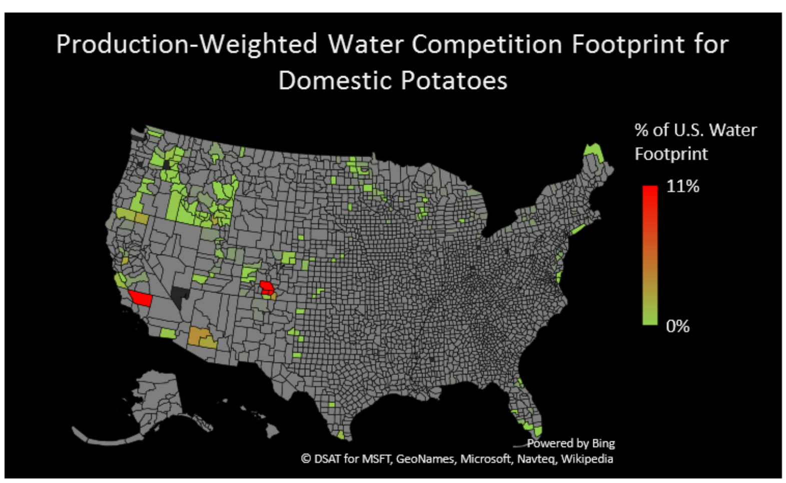
Potatoes

Potatoes are produced primarily in the Pacific Northwest, with 58% of production occurring in Idaho (31%), Washington (21%) and Oregon (6%). Water irrigation requirements are heaviest in western states, and characterized water competition footprints are primarily in Colorado (59% contribution to the national WCF_{pw}) and California (22%). Though Colorado and California produce a combined 11% to U.S. potatoes, they account for 81% of the total water crop water competition footprint. Potatoes have a domestic IWR_{pw} of 74 m^3 / tonne, and a consumed WCF_{pw} of 1,299 m^3-eq / tonne.



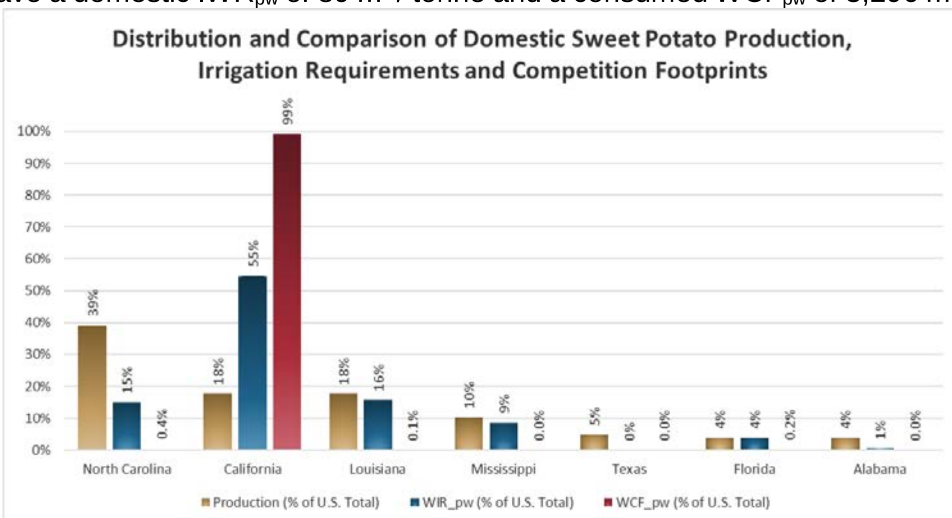


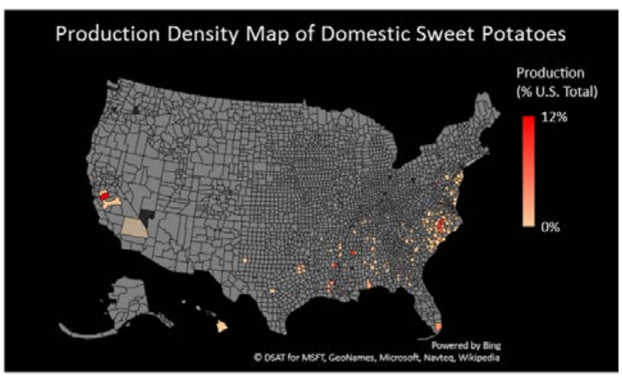


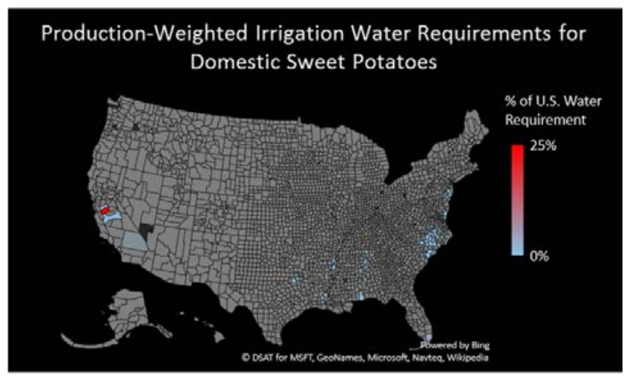


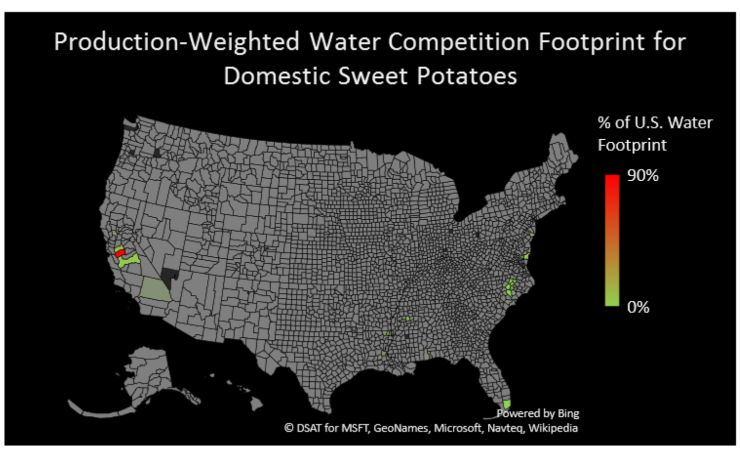
Sweet Potatoes

Sweet potatoes are primarily produced in North Carolina (39% of domestic production), California (18%) and Louisiana (18%), with less than 25% of remaining production distributed among six other states. Upon applying water irrigation requirements to production totals, irrigated water use is centralized in California and North Carolina. Once water characterization factors are applied, California contributes 99% of water competition impacts towards the crop's domestic WCF_{pw}. The production of sweet potatoes in other regions having abundant freshwater supply contributes to this disproportionate share of water competition in California. Overall, sweet potatoes have a domestic IWR_{pw} of 89 m^3 / tonne and a consumed WCF_{pw} of 3,296 m^3-eq / tonne.



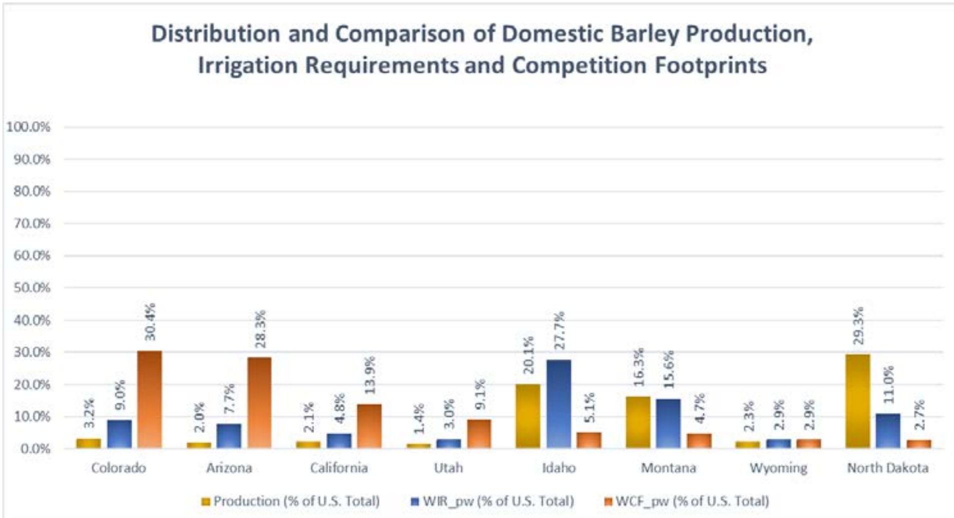


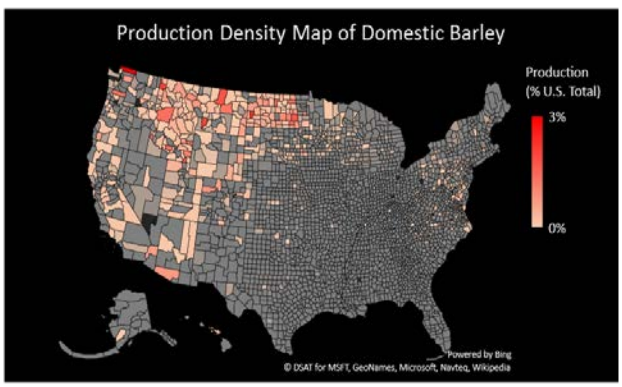


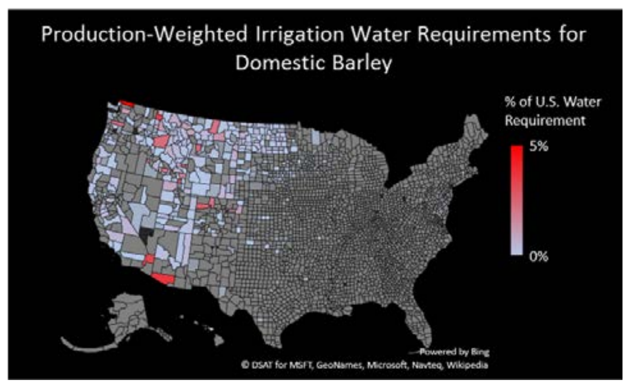


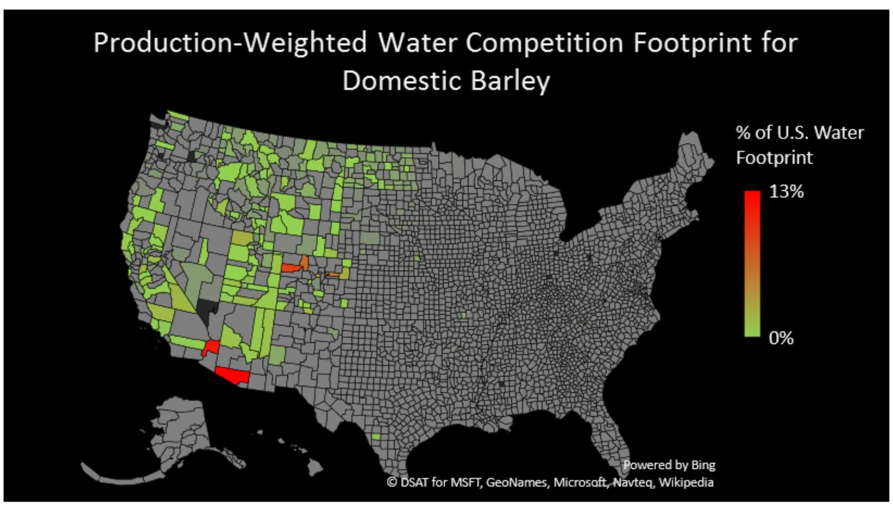
Barley

Barley, similar to wheat, is primarily produced in the western states of North Dakota (29% of domestic production), Idaho (20%), Montana (16%) and Washington (8%). Water irrigation requirements remain consistent for these regions. Calculating water competition using regional characterization factors results in four states contributing over 80% to the national WCF_{pw}, most notably Colorado (30%), Arizona (28%), California (14%) and Utah (9%). Barley has a domestic IWR_{pw} of 185 m^3 / tonne and a consumed WCF_{pw} of 4,679 m^3-eq / tonne, the second highest of the crops assessed.



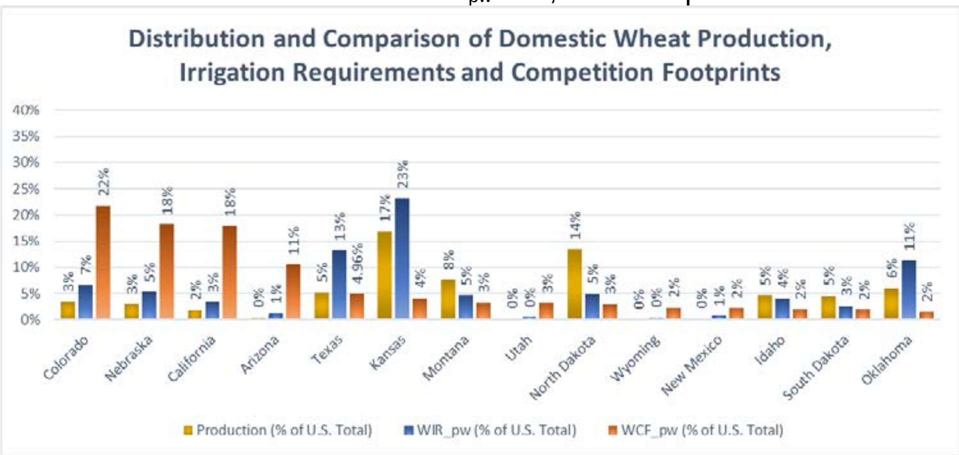


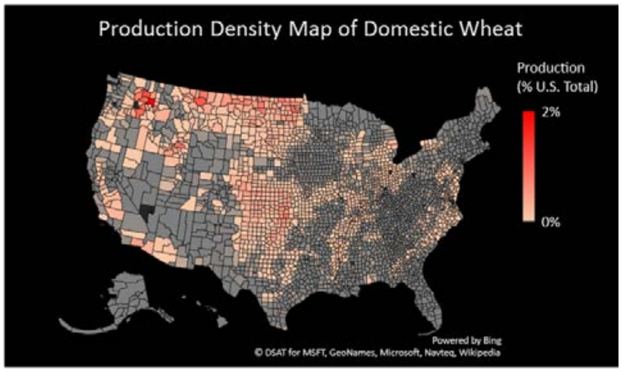


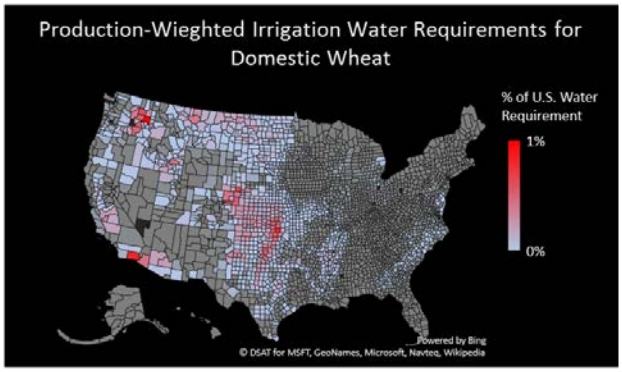


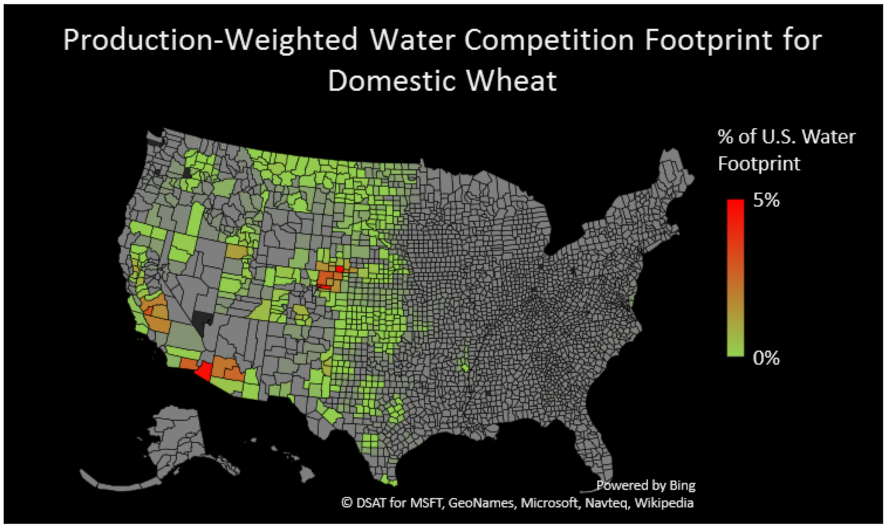
Wheat

Wheat is produced in the majority of U.S. states, with production occurring primarily in western states like Kansas (17%), North Dakota (14%), Montana (8%) and Washington (7%). Irrigation water requirements remain centralized in the same regions providing the majority of production, with denser water uses seen in southern California, Washington, and states across the Great Plains including Kansas, Colorado, Wyoming and Oklahoma. Characterizing water scarcity results in water competition footprints focused in Colorado (22% contribution to the national WCF_{pw}), Nebraska (18%), California (18%) and Arizona (11%). Wheat has a domestic IWR_{pw} of 252 m^3 / tonne and a consumed WCF_{pw} of 2,712 m^3-eq / tonne.



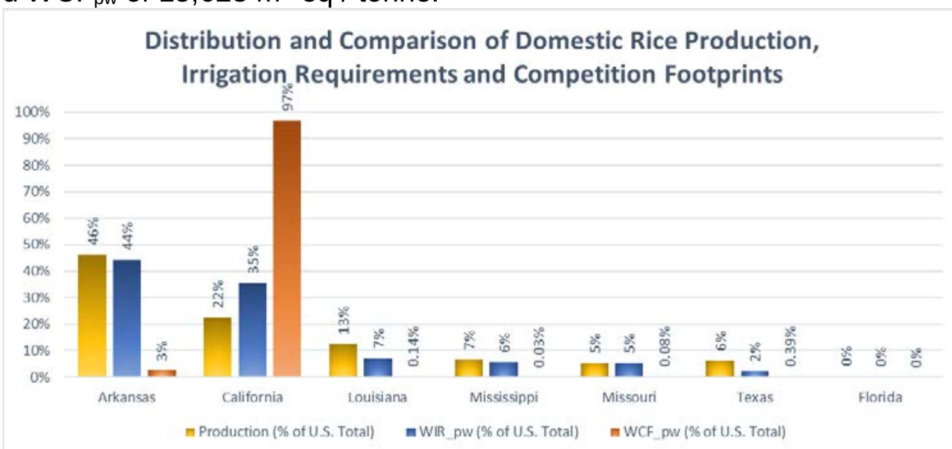


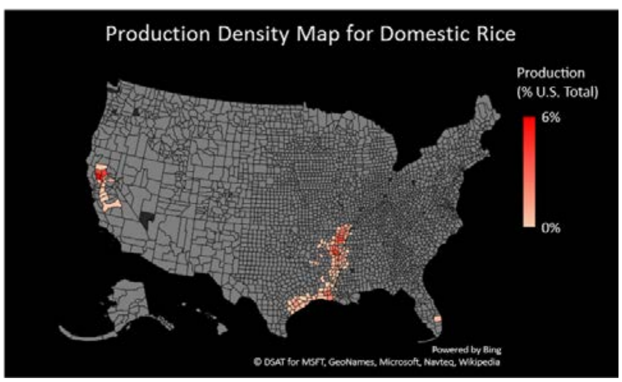


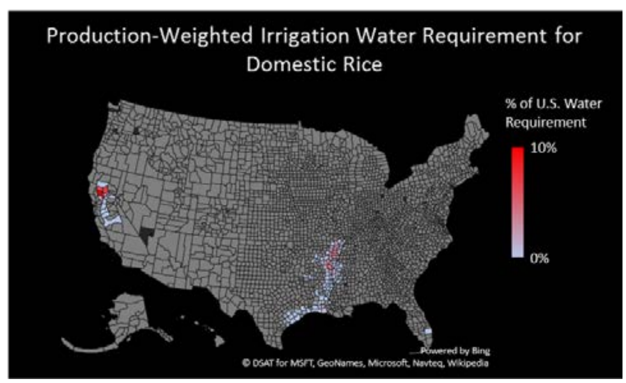


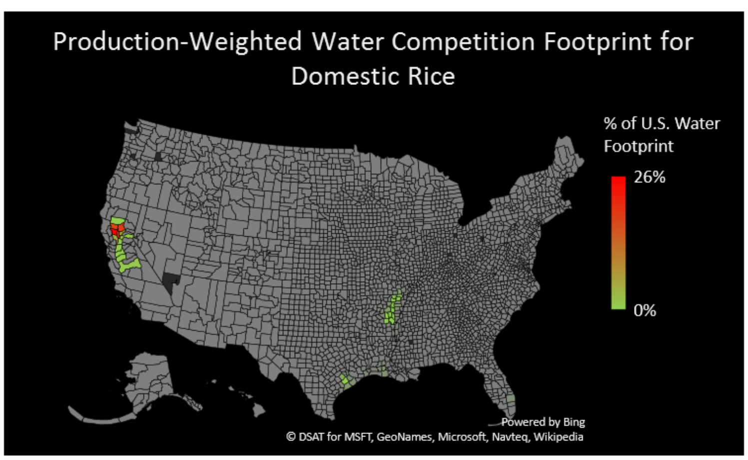
Rice

Rice is produced in California and the southern U.S., with much of the production occurring along the Mississippi River and Gulf of Mexico in Texas and Louisiana. Over 81% of production occurs between Arkansas (46%), California (22%) and Louisiana (13%), with the remaining 19% distributed among Mississippi, Texas and Missouri. Irrigation water requirements occur in the same production states, with increased intensity occurring in California. Once water characterization is applied, California becomes the prominent contributor to the rice water competition footprint (97%). Similar to sweet potatoes, regions growing rice outside of California have less water scarcity issues, giving California a disproportionate contribution towards the crop's domestic WCF_{pw}. Rice has the highest irrigated water requirements and water competition footprint of the crops assessed, with a domestic production weighted IWR_{pw} of 634 m^3 / tonne and a consumed WCF_{pw} of 15,623 m^3-eq / tonne.



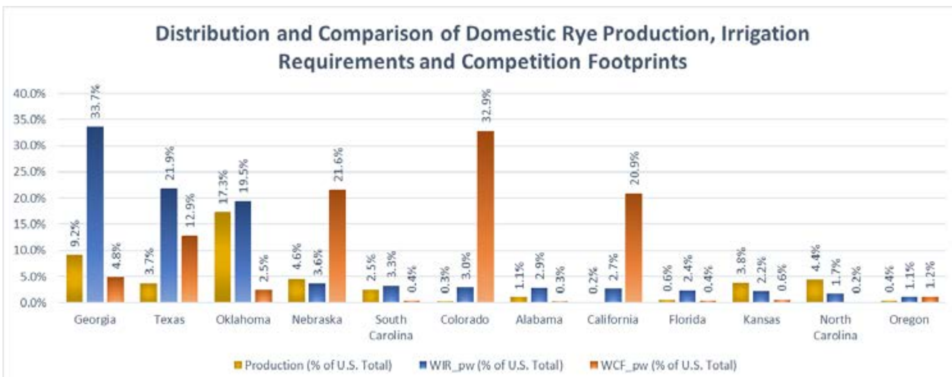


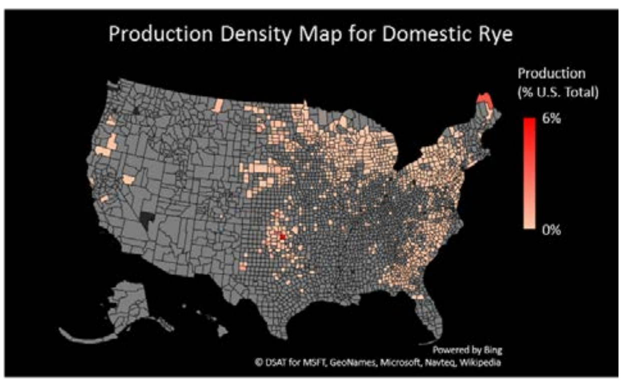


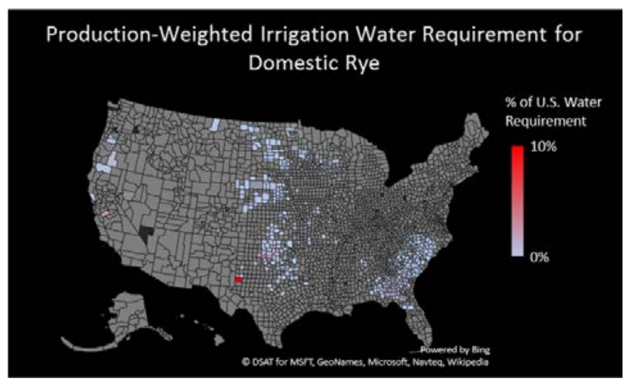


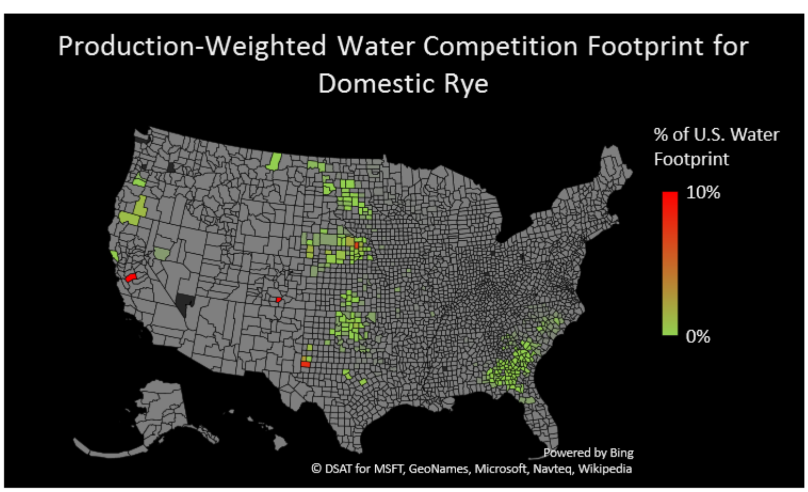
Rye

Production of domestic rye is distributed widely across the U.S., with majority of production occurring in South-East and Mid-West states. Oklahoma is the largest rye producing state (17% of national production), with remaining production occurring in Georgia (9%), Wisconsin (6%), and remaining amounts distributed between 30 other states. Irrigation water requirements for rye are similarly distributed, with Georgia (34% of national IWR_{pw} for rye), Texas (22%) and Oklahoma (20%) using the most irrigated water of all rye producing states. Once water use is characterized, however, Colorado becomes the primary contributor to the rye national water competition footprint (33%), though the state only produces approximately 0.3% of the nation's crop. Other states with high competition footprints include Nebraska (22%of national competition footprint), California (21%), and Texas (13%). The domestic production weighted IWR_{pw} for rye is 212 m^3 / tonne, and a consumed WCF_{pw} of 844 m^3-eq / tonne, which is one of smallest competition footprints of the crops studied.



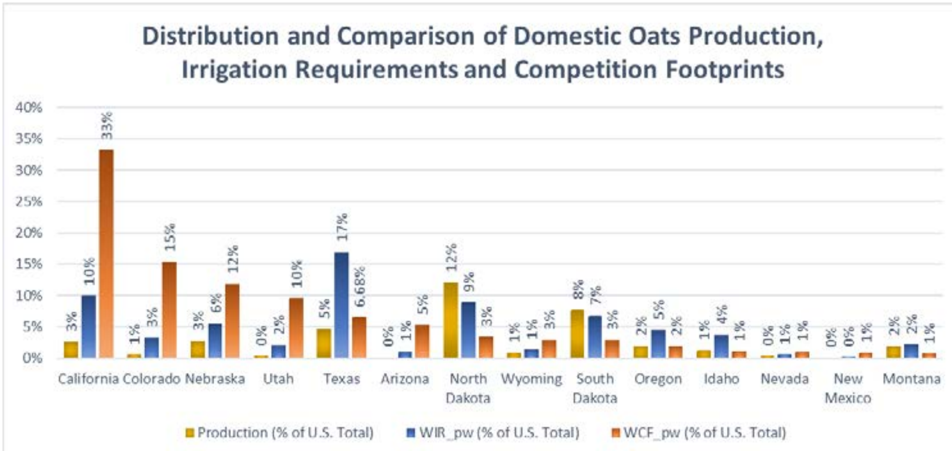


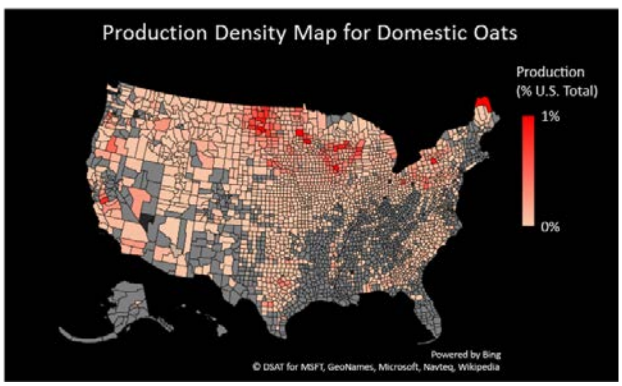


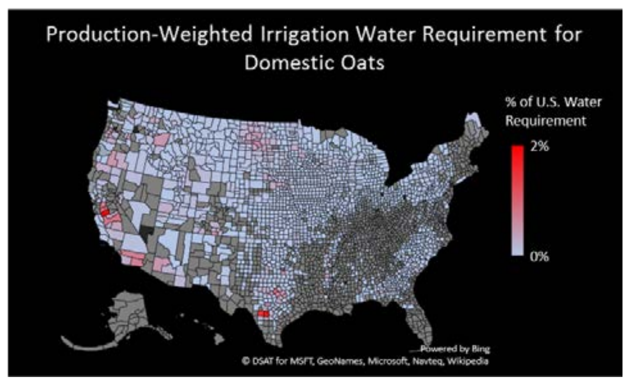


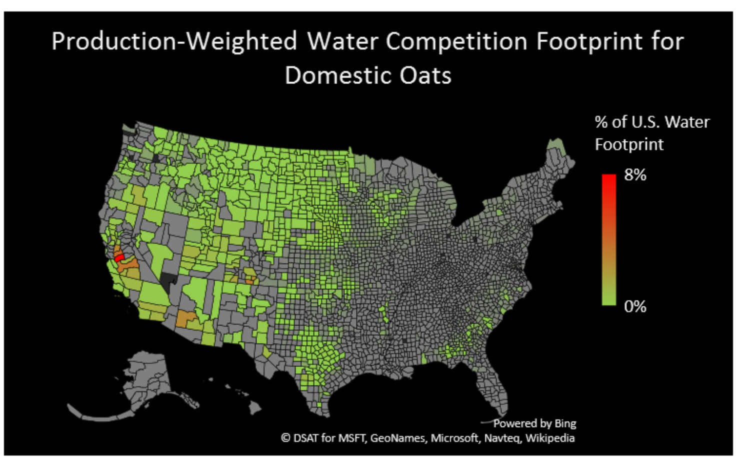
Oats

Oats, similar to rye, has a dispersed production profile throughout the U.S., with primary production occurring in Mid-West states like North Dakota (12% of national production), Wisconsin (12%), Minnesota (11%), Iowa (8%) and South Dakota (5%). Water irrigation requirements are focused in Texas (17% of national IWR_{pw}), California (10%), North Dakota (9%) and South Dakota (7%). Characterization of water requirements shifts all competition footprints to the west, with California (33% of national WCF_{pw}), Colorado (15%), Nebraska (12%) and Utah (10%) ranking highest among states with competition footprints for oats. The domestic production weighted IWR_{pw} for rye is 159 m^3 / tonne, and a consumed WCF_{pw} of 1,751 m^3-eq / tonne.









Sugar beets

Sugar beets have a definitive grouping of production regions throughout the U.S., with Minnesota (33% of national production), Idaho (18%), North Dakota (17%) and Michigan (12%) producing the highest quantities of sugar beets nationally. Irrigation requirements, however, are highest in Iowa (43% of national IWR_{pw}) and western states with lesser quantities of production, most notably California (22%), Colorado (6%) and Nebraska (6%). Water competition among sugar beet producing states are in the same heavy irrigation regions, with California (55% of national WCF_{pw}), Colorado (16%), Nebraska (13%) and Idaho (6%) providing the greatest competition impact nationally. Sugar beets have the lowest domestic IWR_{pw} and consumed WCF_{pw} of the 10 crops studied, with a domestic production weighted IWR_{pw} of 36 m^3 / tonne and a consumed WCF_{pw} of 704 m^3-eq / tonne.