Sustainable Cities and Society 50 (2019) 101621

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Exposure of urban food–energy–water (FEW) systems to water scarcity

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ARTICLE INFO

Keywords:
Virtual water
Water scarcity
Urban water
Food–energy–water nexus

ABSTRACT

Income and population growth increase demands for commodities such as food, energy, and water in cities. Water resources are used outside of cities to produce the food and energy goods that are eventually consumed in cities. In this way, urban water scarcity is impacted directly by local water shortages and indirectly by water scarcity in locations along the supply chain. Both direct and indirect water scarcity risks have important implications for urban water, food, and energy security. In this study, we develop a novel metric of the urban food–energy–water (FEW) nexus that quantifies both direct and indirect water scarcity exposure to urban areas. We quantify and visualize direct and indirect FEW water scarcity for 69 metropolitan statistical areas within the continental United States. We show that cities typically import commodities from nearby locations with similar water resource constraints, and generally have similar local and indirect water scarcity. In particular, cities in the western United States have scarce local water resources and also import commodities from other water-scarce western locations. This study improves our understanding of water scarcity exposure of critical food and energy resources in U.S. urban areas, enabling policy makers to improve the reliability of urban food and energy receipts.

1. Introduction

Global energy demand and food production are projected to increase within the next 30 years by 37% and 71%, respectively (Dubois, 2011; International Energy Agency (IEA), 2014). These increased resource demands will be largely consumed within urban environments, where a majority of the world's population now lives (United Nations, Department of Economic & Social Affairs, 2017). To cope with increasing resource demands, regions producing food, fuel, and electricity often overexploit natural resources, exacerbating their local water scarcity (Kennedy, Cuddihy, & Engel-Yan, 2007; Marston, Konar, Cai, & Troy, 2015; Mortsch & Quinn, 1996). The overexploitation of water resources in water-scarce environments creates vulnerabilities to consumers due to an eventual reduction in production from unsustainable practices (Marston et al., 2015). Numerous regions of the world experience severe water scarcity throughout the year due to the temporal and spatial variability in the availability of water resources (Bhaskar, Jantz, Welty, Drzyzga, & Miller, 2016; Hoekstra, Mekonnen, Chapagain, Mathews, & Richter, 2012; Mekonnen & Hoekstra, 2016; Oki & Kanae, 2006; Zhang, Yang, & Shi, 2011; Zhao et al., 2016). Securing urban direct water resources is an important component of urban resilience and ensuring the future of cities (Jaramillo & Nazemi, 2018; Nazemi & Madani, 2018N, 2018a, 2018z, 2018e, 2018m, 2018i and Madani, 2018; Nazemi & Madani, 2018N, 2018a, 2018z, 2018e, 2018m, 2018i and Madani, 2018). However, beyond direct urban water resources, virtual water accounts for the water consumed in the production of a good, such as food and energy (Allan, 1998), which can indirectly expose consumers to water scarcity concerns. While several studies have evaluated local urban water scarcity (e.g., Flörke, Schneider, & McDonald, 2014; Padowski & Jawitz, 2012), we undertake a more holistic assessment of a city's water scarcity exposure by evaluating local water scarcity and non-local, indirect water demands. Using existing records of intra-national food and energy movements and consumption, along with modeled estimates of their associated virtual water, we create a novel, integrated food–energy–water (FEW) metric that enables comparison and benchmarking of cities' local and indirect water scarcity, using cities in the United States as an example.

Cities require inflows of food and energy, both of which have embedded water resources in various stages of the supply chain (D'Odorico et al., 2017; Fulton & Cooley, 2015; Hoekstra, Chapagain, Aldaya, &

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https://doi.org/10.1016/j.scs.2019.101621
Received 7 December 2018; Received in revised form 19 April 2019; Accepted 20 May 2019
Available online 23 May 2019

Mekonnen, 2009; Stillwell, King, Webber, Duncan, & Hardberger, 2011; Vora, Shah, Bilec, & Khanna, 2017). The interdependence of food, energy, and water resources along each supply chain defines a food–energy–water nexus (Bazilian et al., 2011; D'Odorico et al., 2018; Paterson et al., 2015). Water is needed in the growing of food, cooling of thermoelectic power plants, and in the extraction and refinement of primary fuels. Additionally, energy is required to treat and pump water resources and transport food. Some food products and wastes can be converted into biofuels. Previous studies have coupled virtual water concepts with the movement of food and other resources at the global scale (Carr, D'Odorico, Laio, & Ridolfi, 2013; Dalin, Konar, Hanasaki, Rinaldo, & Rodriguez-Iturbe, 2012; Konar, Dalin, Hanasaki, Rinaldo, & Rodriguez-Iturbe, 2012), national scale (Dang, Lin, & Konar, 2015; Marston & Konar, 2017), and, more recently, at urban scales (Vanham, 2016; Vanham & Bidoglio, 2014; Vanham, Mak, & Gawlik, 2016; Vanham, Del Pozo et al., 2016; Ahams et al., 2017; Chini, Konar, & Stillwell, 2017; Rushforth & Ruddell, 2016). A recent publication has evaluated how varying diets change the water footprint of British, French, and German cities (Vanham, Comera, Gawlik, & Bidoglio, 2018). However, to our knowledge, no studies have combined water scarcity metrics to urban water footprints for multiple cities. It is important to develop integrated frameworks that relate all resources within the FEW nexus with a common metric, in this case, water scarcity. By quantifying the impact of water scarcity on the food, energy, and water resources of cities, we provide a novel metric to comprehensively evaluate the urban FEW nexus.

Building on previous work focused on urban water footprints in the United States (Chini, Konar, et al., 2017), we evaluate and compare local water scarcity and indirect water scarcity at the locations that produce food and energy consumed in urban environments. Our analysis builds on urban resource flows and water scarcity literature by answering three questions: (i) *How and to what extent are the food, fuel, and electricity consumption of cities in the United States exposed to water scarcity, either directly or indirectly?*; (ii) *How does the local water scarcity of each U.S. city compare with its indirect water scarcity?*; and (iii) *What commodities and production locations contribute the most to urban indirect water scarcity?* Answering these questions identifies important relationships between water scarcity at production locations and urban consumption, an underdeveloped research area in the food-energy-water nexus. In this work, we account for the local and indirect water scarcity of 69 U.S. cities using metropolitan statistical areas (MSAs) and material flows defined in the U.S. Census Bureau's Commodity Flow Survey (CFS) for the year 2012. The results of this study provide greater understanding of local and indirect water scarcity for urban areas across the United States.

2. Background

2.1. Water footprints

The water footprint of products includes three separate consumptive components: blue (surface water and groundwater), green (rainwater), and grey (water to assimilate pollutants) water (Hoekstra et al., 2009). Water is needed to irrigate crops, raise livestock, as well as assimilate fertilizers and other pollutants that subsequently enter waterways (Chukalla, Krol, & Hoekstra, 2018; Davis et al., 2016; Mekonnen & Hoekstra, 2010a, 2010b). Global water footprint studies have determined that approximately 90% of global water resources are solely dedicated to food production (Chang, Li, Yao, Zhang, & Yu, 2016; Hoekstra & Mekonnen, 2012). The United States is the largest trader of virtual water, exporting over 165 km^3 of virtual water, annually (Konar et al., 2011). Previous studies have highlighted the significant amount of water embodied in food trade between countries (Hoekstra & Hung, 2005; Konar et al., 2011; Zimmer & Renault, 2003).

Within the United States, high production states, such as Texas, California, and Illinois, annually transfer over 75 km^3 of water for food (Dang et al., 2015). Urban water footprinting studies have found that the water footprints of U.S. cities are largely dominated by their water-for-food demands (Ahams et al., 2017; Chini, Konar, et al., 2017). Water scarcity and droughts further increase the reliance of food production on blue water resources, especially groundwater (Marston & Konar, 2017). While the majority of U.S. food production is rainfed (green water) (Marston, Ao, Konar, Mekonnen, & Hoekstra, 2018), there is significant opportunity cost of allocating surface water and groundwater (blue water resources) for irrigation (Fulton, Cooley, & Gleick, 2014; Konar et al., 2012).

Additionally, energy and electricity resources both have a blue water footprint (Grubert & Sanders, 2018). Water is consumed in the generation of electricity (e.g., Marsh & Sharma, 2007; Sanders, 2014; Stillwell et al., 2011) and extraction/refinement of primary fuels (e.g., Mielke, Anadon, & Narayanamurti, 2010; Wu, Mintz, Wang, & Arora, 2009). Thermoelectric power plants use water for cooling purposes and withdraw more water than any other sector in the United States (Maupin et al., 2014). Additionally, hydropower production is increasingly recognized as a large water consumer as the impounded water evaporates (Grubert, 2016; Mekonnen & Hoekstra, 2012). On the other hand, most renewable energy generation technologies (such as wind and photovoltaic solar) require no direct water to produce electricity (Peer & Sanders, 2018). Some U.S. cities import over 50% of their electricity, depending on water resources for electricity generation from locations outside of the city boundary (Cohen & Ramaswami, 2014). To determine the water footprint of cities from electricity, previous work has utilized state boundaries (Bartos & Chester, 2014; Chini, Konar, et al., 2017; Denooyer, Peschel, Zhang, & Stillwell, 2016; Grubert & Webber, 2015; Stillwell et al., 2011), regional interconnections (Cohen & Ramaswami, 2014; Ruddell, Adams, Rushforth, & Tidwell, 2014), the county scale (Rushforth & Ruddell, 2018), river basin scale (Kelley & Pasqualetti, 2013), or a radius from the city (Chini, Schreiber, Barker, & Stillwell, 2017). Water scarcity issues in the form of drought and heat waves could curtail or shut down generation at power plants (Behrens, van Vliet, Nanninga, & Dias, 2017; Lubega & Stillwell, 2013), highlighting the need to incorporate water scarcity into studies of the food–energy–water nexus. In this study, we analyze the indirect water scarcity of urban energy consumption in two separate categories: the transfers of primary fuels and the generation of electricity.

2.2. Water Scarcity Metrics

The Millennium Ecosystem Assessment of 2005 estimates that half of the global population will live in water-scarce river basins by 2025 (Wang & Blackmore, 2009). Over the past 20 years, there have been a multitude of water resources vulnerability metrics produced that evaluate the many uses of water, including human and environmental demands (Brown & Matlock, 2011). One of the most widely used indicators for water scarcity is the Falkenmark indicator, which is the fraction of total annual runoff available for human consumption (Falkenmark, 1989). Additional metrics include scarcity based on basic human needs (Gleick, 1996); metrics that incorporate hydrology, environment, life, and policy, under a pressure-state-response framework (Chaves & Alipaz, 2007); and the Water Supply Stress Index (WaSSI) based on U.S. Geological Survey 8-digit hydrologic unit codes (McNulty, Sun, Myers, Cohen, & Caldwell, 2014). We use the water scarcity index (WSI) developed by Mekonnen and Hoekstra (2016), which evaluates the blue water scarcity of a particular region, consistent with our approach to only include blue water footprints of products. WSI values, ranging from 0 to 10, are at a 30 × 30 arc minute grid scale, which represents the highest spatial resolution water scarcity values currently available (Vanham, Hoekstra et al., 2018). These WSI grids are a measure of temporally averaged (1996–2005) blue water (surface water and groundwater) available for consumption. Specifically, WSI is calculated as the ratio of a grid cell's blue water footprint to its water available for consumption, accounting for environmental flow requirements (assumed to be 80% of natural flows). A WSI below 1.0 indicates a local water footprint lower than 20% of natural flows and low water scarcity. WSI values exceeding 1.0 indicate some degree of local water scarcity and modified runoff, while WSI values above 2.0 indicate severe water scarcity (Mekonnen & Hoekstra, 2016).

3. Methods

3.1. Data sources

The commodity flow survey (CFS) provides the data necessary to determine flows of food and fuel products to each MSA (United States Census Bureau (USCB), 2012a). The CFS is a pentannual database compiled by the U.S. Census Bureau and the Bureau of Transportation Statistics and provides information on commodity transfers within the United States. These transfers are classified based on the Standard Classification of Transported Goods (SCTG) and include information on origin, destination, weight, mode of transport, and dollar value. We build on work by Chini, Konar, et al. (2017) and develop the blue water footprints of MSAs including food and fuel for the year 2012. The blue water content of a product, defined as the volume of blue water consumed to produce a unit weight of a good (Marston et al., 2018), is computed for all food and fuel commodity groups following Dang et al. (2015) and Chini, Konar, et al. (2017). The water content of a commodity group (e.g., cereal grains) for each U.S. state is calculated as the average water content of each subitem of that group (e.g., wheat, corn, rye), weighted by the total production of each component in each respective state using the U.S. Department of Agriculture's Census of Agriculture. Water content values for subitems of food commodities originate from Mekonnen and Hoekstra (2010a), Mekonnen and Hoekstra (2010b), Mekonnen and Hoekstra (2011) and Mubako (2011) at the state spatial scale. To quantify water consumption associated with electricity transfers across the United States, we adapt the methods from Chini, Djehdian, Lubega, and Stillwell (2018). This study uses electricity transfers between power control areas (PCAs) to determine more spatially refined water footprints of electricity. The cities included within this study were then paired with their respective PCA to identify an appropriate blue water content of electricity. PCAs serving cities were identified through searches of governmental and utility websites. If no direct reference to a city was found, the closest PCA in the region was attributed. To determine the blue water footprint of each city for electricity, state level annual electricity consumption data (Energy Information Administration, (EIA, 2012) are normalized using populations of cities (see supporting information in Chini, Konar, et al. (2017) for population information). Electricity data from the year 2012 are utilized to match the food flows from the 2012 CFS.

Water scarcity values, as mentioned in Section 2.2, were taken from an analysis of blue water availability across the globe by Mekonnen and Hoekstra (2016). These values range from 0 to 10 and consider environmental demands of blue water resources. We modify the proposed scale of water scarcity (expanding from four to five categories) and use these descriptors to illustrate the indirect and local water scarcity of U.S. cities. Table 1 provides the descriptors, values of water scarcity, and associated color scale utilized in figures of results.

3.2. Calculating local and indirect water scarcity of cities

We quantify, compare, and visualize cities' indirect water scarcity (IWS), including food, fuel, and electricity imports, and local water scarcity (LWS). Local water scarcity is defined as the value of WSI at the centroid of each city. It is a measure of the blue water resources available for consumption in a city's immediate environment. Indirect water scarcity expands on the understanding of urban water resources to account for water embedded in various products imported into the city. The water scarcity in the location of production of these materials (food, fuel, and electricity) is then transferred, indirectly, to the city and its residents. Using this concept of transferring water scarcity, we define urban indirect water scarcity as the weighted average of water scarcity at the location of production with respect to the blue water footprints of imports, see Eq. (1). These definitions build on a previous study by Rushforth and Ruddell (2016) and their work on hydro-economic vulnerability of Flagstaff, AZ.

Table 1
We divide water scarcity index (WSI) values into five bands, refining previously defined intervals from Mekonnen and Hoekstra (2016). The band 'extreme' is added in this analysis for clarity in values.

Water Scarcity	WSI Values	Color
Low	< 1.0	(blue)
Moderate	1.0–1.5	(grey)
Significant	1.5–2.0	(pale yellow)
Severe	2.0–5.0	(orange)
Extreme	> 5.0	(red)

$$\mathrm{IWS} = \left[\frac{V_{\mathrm{Food}}}{V_{\mathrm{Tot}}} \times \mathrm{IWS}_{\mathrm{Food}}\right] + \left[\frac{V_{\mathrm{Fuel}}}{V_{\mathrm{Tot}}} \times \mathrm{IWS}_{\mathrm{Fuel}}\right] + \left[\frac{V_{e^-}}{V_{\mathrm{Tot}}} \times \mathrm{IWS}_{e^-}\right] \tag{1}$$

where,

$$V_{\mathrm{Tot}} = V_{\mathrm{Food}} + V_{\mathrm{Fuel}} + V_{e^-} \tag{2}$$

and V_{Food}, V_{Fuel}, and V_{e^-} refer to the virtual water imports to each city associated with food, fuel, and electricity, respectively. We approximate V_{e^-} as the net water intensity of electricity (m^3/MWh) of the PCA that serves the city from Chini et al. (2018), multiplied by the state-level annual electricity consumption per capita and city population (E, 2012n, 2012e, 2012r, 2012g, 2012y Information Administration (EIA), 2012; United States Census Bureau (USCB), 2012). IWS_{Food} and IWS_{Fuel} are calculated as:

$$\mathrm{IWS}_{\mathrm{Food}} = \mathrm{IWS}_{\mathrm{Fuel}} = \sum_{\mathrm{State}} \left[\frac{V_c^{S \to \mathrm{City}}}{V_c^{\mathrm{Tot}}} \times \mathrm{WSI}_S\right] \tag{3}$$

where $V_c^{S \to \mathrm{City}}$ is the virtual water flow from state S to the city associated with the commodity c. WSI_S is the spatially averaged WSI of state S. V_c^{Tot} is the total virtual water transferred into the city for each commodity group, c. IWS_{Food} and IWS_{Fuel} represent an average of the WSI of each state transferring commodities to the city, weighted by the corresponding relative volume of virtual water transfers. Because state to city level commodity flow data are employed, we do not distinguish where, within each state, food and fuel commodities are produced. The limitations associated with this methodology are further discussed in Section 5.2.

Due to the difference in the resolution of electricity data and fuel/food data, the calculation of IWS_{e^-} differs from that of IWS_{Food} and IWS_{Fuel}. Data for indirect water for electricity transfers are available at a PCA-to-PCA level through the U.S. Federal Energy Regulatory Commission (U.S. Federal Energy Regulatory Commission (FERC), 2017). Additionally, every PCA contains various power plants, each with unique water availability conditions. Each PCA's overall water scarcity index (WSI_{PCA}) is calculated as the average of the WSI at the power plants constituting that PCA, weighted by the annual consumed water of each power plant. The power plants in each PCA are detailed in the eGrid database by the U.S. Environmental Protection Agency and blue water consumption can be found in Form 923 of the Energy Information Administration (E, 2012n, 2012e, 2012r, 2012g, 2012y Information Administration (EIA), 2012; U.S. Environmental Protection Agency (USEPA), 2017). More information on these datasets and their integration can be found in the methods of Chini et al. (2018). Electricity data are from the year 2012 to be consistent with the Commodity

Flow Survey. Each city is assumed to be served by a single PCA. The indirect water scarcity associated with electricity inflows (IWS_{e^-}) of each city is then calculated as the average of WSI_{PCA} values, weighted by the virtual water flow from each PCA to the PCA serving each city, K; see Eq. (4).

$$IWS_{e^-} = \sum_{PCA} \left[\frac{V_{PCA \to K}}{V_{gen,K} + V_{in,K}} \times WSI_{PCA} \right] \quad (4)$$

where, $V_{PCA \to K}$ is the virtual water flow from each PCA to K, $V_{gen,K} + V_{in,K}$ is the sum of blue water consumed within K and the virtual water flows to K from other PCAs.

4. Results

4.1. Comparing the local and indirect water scarcity of cities

Cities with indirect water scarcity values above 1.0 are at various levels of water scarcity (see Table 1), while those with water scarcity values below 1.0 import commodities from locations with low water scarcity. Comparing the difference between cities' local and indirect water scarcity gives insight as to how efficiently those cities offset local water scarcity through commodity imports from more or less water-scarce locations; see Fig. 1. Cities in the western United States tend to have higher water scarcity (local and indirect) than those in Midwestern and Eastern states. Cities with the most severe local and indirect water scarcity are concentrated in the southwestern United States. Cities such as El Paso (TX), Laredo (TX), Phoenix (AZ), Las Vegas (NV), Tucson (AZ), and Corpus Christi (TX) have extreme values of local water scarcity. The latter four cities are also among the ten cities with highest indirect water scarcity, importing commodities from locations facing extreme water scarcity; see Table 2.

On the other end of the spectrum, eastern cities like Albany (NY), Rochester (NY), Hartford (CT), and Knoxville (TN) are located within regions with more abundant local blue water resources and also have low local and indirect water scarcity values. Fig. 2 shows a scatter plot of the local versus indirect water footprint of each city in our analysis. We find that 35 out of the 69 studied cities have local and indirect water resources that both have low water scarcity. Additionally, seven cities had severe water scarcity for both local and indirect water resources. Overall, we find that, in most cases, cities with local water scarcity tend to import commodities from locations that also have blue water scarcity.

A few cities show particularly large discrepancies between their local and indirect water scarcity; see Table 2. Laredo (TX) and El Paso (TX) have extreme local water scarcity, and are able to offset further water scarcity by importing their commodities from less water-scarce locations. El Paso (TX) has the largest inland desalination plant in the world, and receives 55% of its food-related indirect water imports from Missouri, which has, on average, a lower water scarcity. Importing commodities from less water-scarce locations decreases exposure to indirect water scarcity. Las Vegas (NV) and Laredo (TX) both import 46% of their respective virtual water for food from within Texas, resulting in a higher indirect water scarcity. On the other end of the spectrum, cities like Austin (TX), Beaumont (TX), and Omaha (NE) have low local water scarcity but have severe indirect water scarcity. Both Austin (TX) and Beaumont (TX) are located in regions of Texas that have low local water scarcity, but over 90% of their virtual water resources are produced in-state, which has a higher average indirect water scarcity. Omaha (NE) is also located in an area of low water scarcity, but imports 95% of its food (likely including large amounts of animal feed) and fuel from the rest of Nebraska and Wyoming, both of which are, on average, high water-scarce states. It is important to note,

Table 2
Cities with highest and lowest local and indirect water scarcity. Cities with a larger LWS than IWS offset water scarcity by importing commodities from locations of lower water scarcity. Most cities with high LWS and IWS are in the Southwestern United States.

Rank	City	LWS	Rank	City	IWS
1	Phoenix (AZ)	6.76	1	Corpus Christi (TX)	4.52
1	El Paso (TX)	6.76	2	Austin (TX)	4.51
1	Las Vegas (NV)	6.76	2	San Antonio (TX)	4.51
1	Tucson (AZ)	6.76	3	Dallas (TX)	4.20
1	Corpus Christi (TX)	6.76	4	Houston (TX)	4.17
1	Laredo (TX)	6.76	5	Tucson (TX)	3.85
66	Mobile (AL)	< 0.01	66	Albany (NY)	0.10
67	Detroit (MI)	< 0.01	67	Rochester (NY)	0.08
68	Louisville (KY)	< 0.01	68	Hartford (CT)	0.06
69	Cincinnati (OH)	< 0.01	69	Knoxville (TN)	0.06

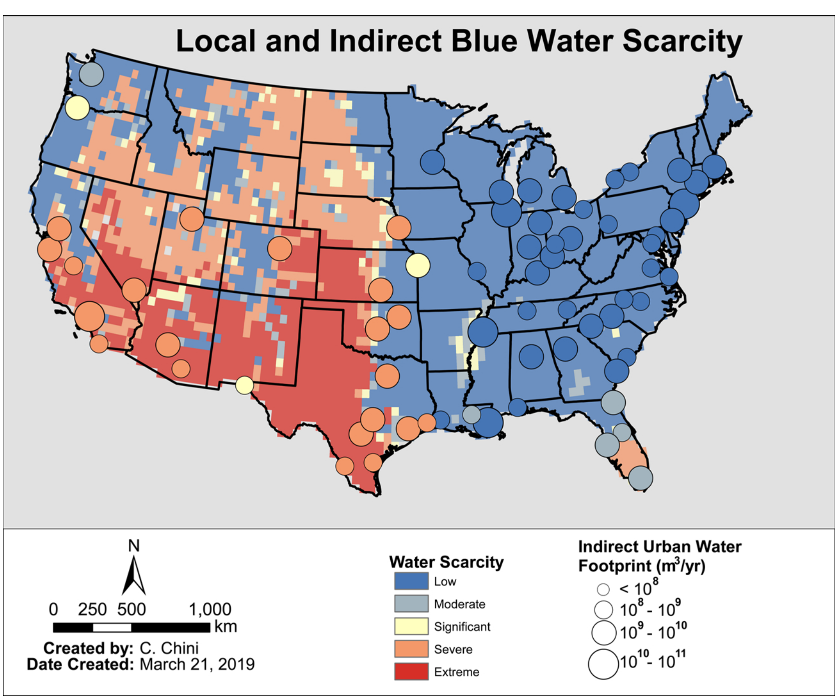

Fig. 1. Indirect water scarcity and blue water footprint are mapped against local water scarcity from Mekonnen and Hoekstra (2016). Local water scarcity is a measure of the city's local water resources, while urban indirect water scarcity is a measure of the water scarcity at the locations that produce commodities that are then imported. Circle sizes represent cities' indirect blue water footprints.

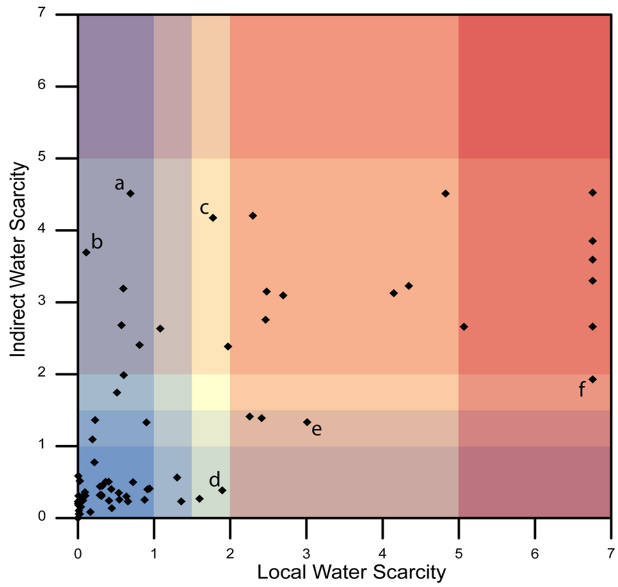

Fig. 2. Most cities have local and indirect water resources that are similar in water scarcity. Background colors represent the different thresholds of water scarcity. See Table 1 for the water scarcity labels. (a: Austin, TX; b: Beaumont, TX; c: Houston, TX; d: Chicago, IL; e: Tampa, FL; f: El Paso, TX).

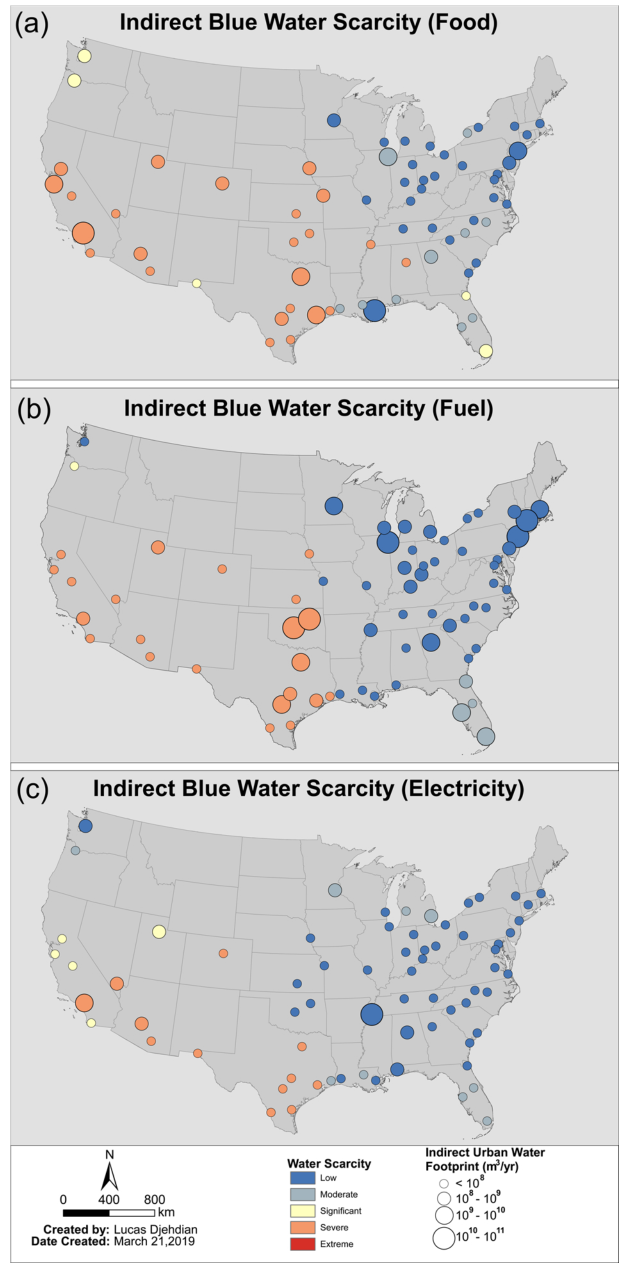

Fig. 3. Indirect water scarcity associated with (a) food, (b) fuel, and (c) electricity imports for different U.S. cities. Color represents IWS values, while size refers to the indirect water footprint of the city associated with each commodity.

however, that geographic averaging of WSI at a state level can add significant uncertainty to a city's indirect water scarcity.

4.2. Resource contributions to urban indirect water scarcity

We visualize the individual indirect water scarcities associated with the imports of food, fuel, and electricity; see Fig. 3. Comparing these contributions of indirect water scarcity, we find that 12 cities have high water scarcity for all three resources. As is the case with cities' overall indirect water scarcity, urban areas in Western states have higher water scarcity associated with each commodity than those in the Midwestern and Eastern United States. In comparison, Eastern cities such as New York (NY), Baltimore (MD), and Charleston (SC) have IWS_{Food}, IWS_{Fuel} and $\mathrm{IWS}_{\mathrm{e^-}}$ values below 0.50 (low water scarcity) and are, therefore, less likely to incur food, fuel, and electricity import disruptions due to water scarcity at the supply location.

For each city, we also calculate the fraction of indirect water scarcity that is associated with its food, fuel, and electricity imports. Fig. 4 shows these commodity contributions for each city, ordered from left to right by overall increasing indirect water scarcity. Food and fuel imports have a larger influence on indirect water scarcity than electricity imports for most cities. Electricity imports have an overall low influence on the indirect water scarcity of cities; their contribution to indirect water scarcity are less than 30% for 50 of the 69 considered cities; see Fig. 4. For example, while El Paso (TX) has the largest IWS of electricity of all cities, the electricity term of Eq. (1) only makes up 5% of its total indirect water scarcity. This finding emphasizes the importance of quantifying and understanding individual resource contributions to water scarcity. Although cities' water footprints of food and fuel greatly exceed the water footprints of electricity, similar to findings of Chini, Konar, et al. (2017), imports of food, fuel, and electricity all have non-negligible impacts in the indirect water scarcity of cities.

4.3. Hotspots of urban indirect water scarcity

In our analysis, we find that cities tend to import virtual water from nearby states with similar water scarcity as the cities themselves. This finding is in accordance with assertions that distance is a key factor in trade and supply chains (Maier, Lence, Tolson, & Foschi, 2001). Specifically, over 85% of the water footprints of food and fuel of water-scarce California (including, Fresno, Sacramento, San Francisco, and San Diego) originate in California. In addition, over 50% of these cities' electricity water footprints are from the California Independent System Operator (CAISO). Similarly, we find that nearly 90% of food-derived and fuel-derived indirect water imports of Corpus Christi (TX), Dallas (TX), Austin (TX), and San Antonio (TX) originate in Texas. The water footprint of electricity of these Texas cities originates solely in the Electric Reliability Council of Texas, covering most of Texas. Conversely, the same trend is observed for cities with low indirect water scarcity. New York City receives 92% of its water footprint of electricity from the New York Independent System Operator, and 55% of its food and fuel water footprints from either New Jersey or New York. Generally, we find that commodity transfers occur in short distances

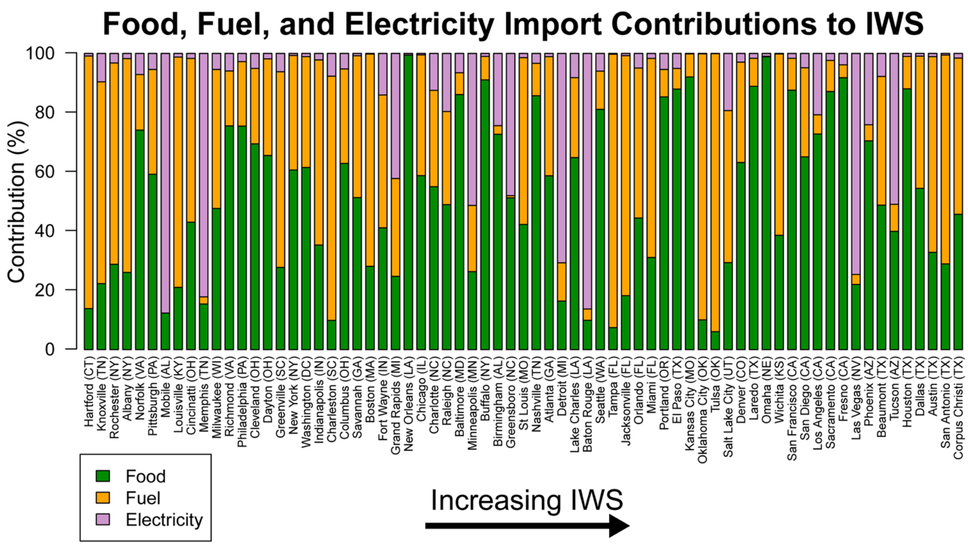

Fig. 4. The percent contributions of IWS_{Food}, IWS_{Fuel}, and IWS_{e}– to indirect water scarcity of cities, ordered from left to right in overall increasing IWS. Although food and fuel contributions dominate the water scarcity of most cities, electricity imports also have a significant impact in urban water scarcity.

between nodes of similar water resource constraints, creating similar scarcities between local and indirect water resources.

In addition to quantifying the contribution that each imported commodity has on the indirect water scarcity of cities, we determine the origin locations of production driving water scarcity; see Fig. 5. In our analysis, food and fuel production are assumed to occur at a state level. Electricity contributions are aggregated to North American Electric Reliability Corporation (NERC) regions for visualization purposes. Fig. 5 shows the percent contribution of each U.S. state to indirect water scarcity of food and fuel and each NERC region to indirect water scarcity of electricity for the U.S. cities analyzed. The western portion of the country from California to Texas contributes over 65% and 40% of indirect water scarcity of food and fuel, respectively. A similar trend is found for electricity transfers; PCAs in the Western half of the country (Western Electricity Coordinating Council, Texas Reliability Entity), contribute to over 70% of cities' indirect water scarcity of electricity. As a large exporter of coal and a water-scarce state, Wyoming contributes 35% of cities' indirect water scarcity of fuel. California, Texas, and Wyoming are severely water-scarce and are large producers and exporters of commodities, making them hubs of indirect water scarcity.

5. Discussion

5.1. Water scarcity and sustainability

In this analysis, we build on previous studies that determine the water footprint of U.S. cities. Understanding the origin of urban water footprints and the corresponding stress that production puts on the local environment provides an extra layer of information for sustainable management of indirect water resources. Through commodity trades and transfers, water scarcity is also indirectly transferred from the location of production to cities across the United States. Cities typically import commodities from nearby locations with similar water resource constraints and generally have similar local and indirect water scarcity. The proposed method for characterizing water vulnerability within the food-energy-water nexus provides a unifying framework to understand the broader extent of water resources in cities. Including both direct and indirect water footprints and associated water scarcity enables opportunities for water governance strategies to promote sociotechnical transitions that advance urban water sustainability and security. While there are currently no mechanisms in place to enforce broader governance strategies of urban indirect water resources, it is important to begin capturing how cities and their resource demands affect water scarcity outside their boundaries to develop future policies for handling an uncertain future.

Interestingly, the magnitudes of a city's water footprints of food, fuel, and electricity do not necessarily inform their local and indirect water scarcity. Memphis (TN), for example, has by far the highest water footprint of electricity of all cities (11.6 billion cubic meters); however, it has a low water scarcity. As Figs. 1 and 3 show, higher water scarcity is generally found in the Western portion of the country. However, we find that coastal cities have the highest water footprints, consistent with findings from Chini, Konar, et al. (2017). Port cities have a large water footprint because a significant fraction of imported commodities are then exported internationally. Due to its comparative advantage of agricultural production, the United States exports more virtual water associated with food products (165 m^3/year) than any other country (Dang et al., 2015; Konar et al., 2011; Konar, Hussein, Hanasaki, Mauzerall, & Rodriguez-Iturbe, 2013).

In our analysis, we find that the contribution of food, fuel, and electricity imports on indirect water scarcity varies between cities. In particular, food and fuel flows are the main drivers of U.S. cities' indirect water scarcity. Interestingly, no correlation is present between these individual contributions and the city's geographic location. Overall, cities import food, fuel, and electricity from nearby regions with similar local water scarcity conditions as the cities themselves, explaining why most cities tend to have similar local and indirect water scarcity. Water-scarce cities, such as Corpus Christi (TX) and Dallas (TX), import most of their commodities from Texas, which is an overall water-scarce state. Water abundant cities, such as Albany (NY,) import the majority of their food, fuel, and electricity from New York, which is a water abundant state. Similar to our results, previous virtual water network analyses have found shorter travel distance to be a major driver of commodity flows (Fracasso, 2014; Tamea, Carr, Laio, & Ridolfi, 2013). The food and energy supplies of water-scarce cities, dependent on a limited number of nearby production nodes, might be vulnerable to disturbance events such as droughts and heat waves. Understanding network structure of resource supplies to cities could enable greater adaptability in the face of regional drought or long-term climate change. This study illuminates the importance of considering water scarcity in FEW supply chains. Increasing the spatial diversity of producers/providers could be one means to enhance supply chain resilience to (spatially correlated) water stress or hazards.

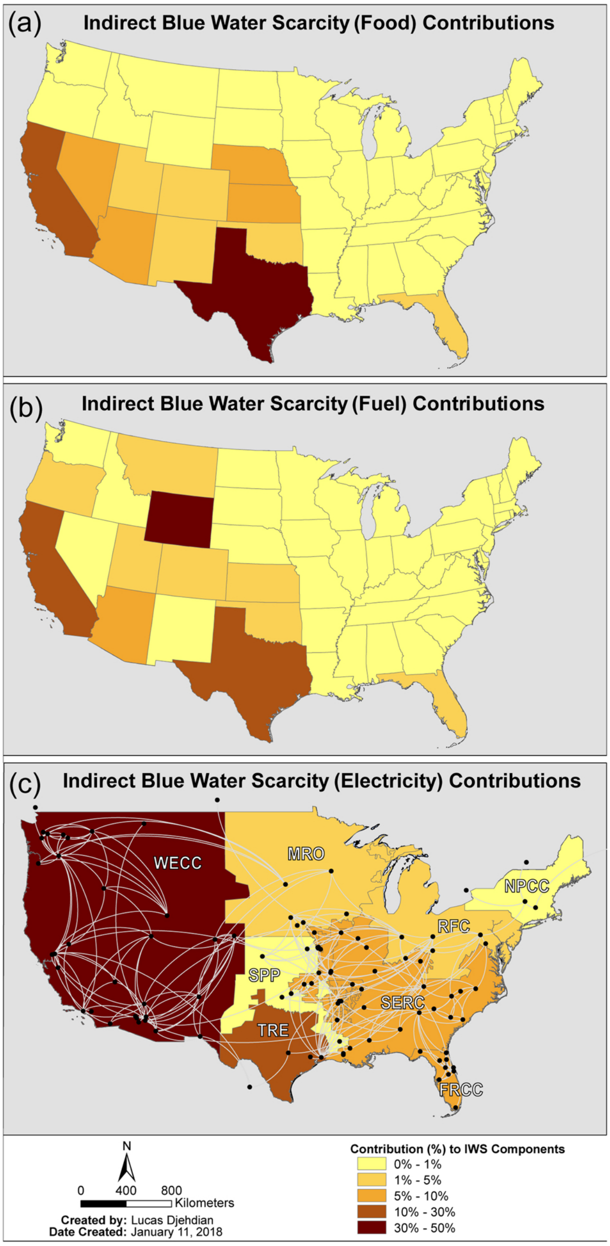

Fig. 5. Map of states' contributions to (a) IWS of food and (b) fuel, and (c) NERC regions' contributions to IWS of electricity for analyzed (aggregated) cities. In (c), black dots and white links correspond to PCAs and the electricity transfers between them, respectively (from Chini et al. (2018)). A darker red color is associated with larger contributions to U.S. urban indirect water scarcity. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5.2. Data and study limitations

Our analysis synthesized data from published academic literature, as well as state, national, and international agency reports. Although our work revealed important trends and relationships between water scarcity and the water footprints of cities, data limitations bring uncertainty into the results. To determine cities' indirect water scarcity associated with electricity imports, we employed data from U.S. governmental entities such as the Energy Information Administration and Environmental Protection Agency (E, 2012n, 2012e, 2012r, 2012g, 2012y Information Administration (EIA), 2012; U.S. Environmental Protection Agency (USEPA), 2017) and the Federal Energy Regulatory Commission (U.S. Federal Energy Regulatory Commission (FERC), 2017), as well as published literature (Grubert, 2016). Governmental data are self-reported and carry uncertainties associated with their origin (Averyt, Macknick, et al., 2013; Peer & Sanders, 2016). There are uncertainties around the CFS as the data are an estimation of flows. The CFS data represent a survey of industrial shipments. Like all surveys (as opposed to a census), it represents a sample of the population and the rescaling of these data to represent the entire shipment population will lead to some inaccuracies. Additionally, there might be some items that are out of scope of the survey (e.g., some farm to distributor shipments), which will lead to a potential underestimation of food/water dependency in our estimates. In this way, our estimates are likely conservative. There is potential for double-counting with the current CFS models, though these are likely to be minimal for the raw agricultural and energy commodities that are the focus of this study.

There is also considerable temporal and spatial inconsistencies between water scarcity and commodity flow data. Water scarcity index values provided by Mekonnen and Hoekstra (2016) have a 30 × 30 arc minute resolution, while commodity transfers (United States Census Bureau (USCB), 2012a) are available at a state-to-MSA scale. Because state-to-MSA commodity transfer data were employed, the water scarcity of food and fuel production nodes are spatially averaged across each state. By doing so, we assume that each state's commodity production is spatially uniform, which follows the approach of Dang et al. (2015) and Chini, Konar, et al. (2017). Although we are able to capture much of the spatial distribution of water scarcity (and its driving mechanisms) in the United States, more developed and resolved water scarcity and commodity flow databases could yield more accurate results.

Additionally, the study only considers domestic flows of food and energy and, therefore, only evaluates domestic water scarcity. There is a smaller fraction of international products imported into cities. These products often could be from water-scarce regions around the globe, such as avocados from Mexico or olive oil from the Mediterranean region. These products represent a relatively small portion (by mass) of overall consumption and, therefore, their exclusion does not overly affect the results.

6. Conclusions

In this paper, we comprehensively quantify both local and indirect water scarcity for 69 of the metropolitan statistical areas of the United States associated with urban food, fuel, and electricity commodity consumption. We develop a novel metric of the urban food-energy-water (FEW) nexus. Our analysis visualizes the susceptibility of U.S. cities' commodity imports to water scarcity. Returning to the three previously posed questions, (i) indirect and local water scarcity of U.S. cities is highly heterogeneous. Additionally, (ii) most cities have similar local and indirect water scarcity, though the degree of indirect water scarcity is not always consistent with the degree of a city's local water scarcity, and (iii) states in the western United States and food commodities contribute the most to urban indirect water scarcity.

The analysis provides information necessary for supply chain managers and planners seeking to ensure the reliability of food, fuel, and electricity access. By quantifying the drivers of urban water scarcity, we find that water-scarce states that produce a large amount of commodities (i.e., Texas, California, Wyoming) are the main contributors to the indirect water scarcity of cities across the United States. Recent droughts in the Midwest and California demonstrated the impacts of this water-related risk on the agricultural industry by causing billions of dollars of damage, tens of thousands of lost jobs, and disruptions in supply chains, affecting critical industries and final consumers (Al-Kaisi et al., 2013; Howitt, Medellí-Azuara, MacEwan, Lund, & Sumner, 2014). Past evidence (Woodhouse & Overpeck, 1998), along with predicted future climate change (Intergovernmental Panel on Climate Change, 2014), suggest future droughts and water scarcity will likely be more severe than what we have experienced in recent history.

Nearly half of the watersheds within the United States will likely experience a decrease in surface water supplies due to climate change, which does not account for the likelihood of greater water scarcity due to increased anthropogenic water use (Averyt, Meldrum, et al., 2013). An understanding and quantification of water scarcity provides a common metric for evaluating water resources with in the food–energy–water nexus, especially within cities.

Our analysis builds on existing water footprint and water scarcity literature by providing tools for food–energy–water nexus studies to better understand how urban commodity flows interact with water scarcity across the United States. As higher resolution water scarcity data become available, indirect water scarcity can be further disaggregated into surface water scarcity and groundwater scarcity. More detailed commodity flow data, similarly, could allow for critical infrastructure in cities' supply chains to be determined to further inform water resource management and policy. Overall, the quantification and visualization of the water scarcity of cities and the factors driving that scarcity can act as a decision-support tool moving forward in sustainable management of the food–energy–water nexus.

Acknowledgements

Communicated to the journal.

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