

**Title:** Assessing water security across scales: A case study of the United States

**Abstract:** Water security is a multi-dimensional concept that varies across spatial scales. However, evaluations tend to focus on a single scale, which can suppress spatial heterogeneity and may not be relevant to the scale of decision making. We have identified four considerations encountered when selecting a scale in water security analyses: (1) the natural scale of phenomena, (2) the scale of data availability, (3) the decision-making scale, and (4) precision versus accuracy. To explore these considerations and how they may impede a multiscale analysis, we have created a water security index comprised of ten sub-indicators focused on system performance and outcomes. These sub-indicators are assembled across three scales: the United States of America and its constituent states and counties. A tiered multiscale analysis was difficult for several reasons, not least because of the challenges of obtaining requisite data. Nonetheless, the analysis has proved to be worthwhile by exposing areas of insecurity within the United States both at the state and county levels, and by demonstrating greater spatial heterogeneity than might previously have been assumed. Combining the sub-national indicators with a more comprehensive national assessment can support decision-making in terms of prioritization of policies and investments to target hotspots of insecurity.

**Keywords:** water security, spatial scale, composite indicator, multiscale analysis, spatial heterogeneity, water security index

## 1. Introduction

Water security was originally conceived in the early 1990s in the context of concerns about water scarcity and its effects on national security (Starr, 1991). It has since expanded to become an all-encompassing concept of water-related concerns and has been defined as “a tolerable level of water-related risk to society” (Grey et al., 2013, p. 2). This definition could be interpreted as the risk a farmer faces when confronted with unreliable irrigation water supplies, the risk a city may face from deteriorating water infrastructure, or the risk a nation may face when dealing with large-scale droughts and other climatic extremes. Each of these situations may be addressed by decision maker(s) across various spatial and temporal scales.

The first and most fundamental question of any security analysis is “security for whom?” (Baldwin, 1997, p. 13). Grey et al.’s 2013 definition is not alone in leaving this fundamental question open-ended, with several other water security definitions doing the same (UN, 2000; Grey and Sadoff, 2007; UN-Water, 2013). This ambiguity means that the concept can be tailored to different contexts, but also leads to the concept of water security repeatedly being framed and evaluated in diverse ways.

Water security studies have been on the rise since the early 1990s (Cook and Bakker, 2012; Gerlak et al., 2018). Yet, only a small portion of these studies assess water security in the broadest sense of the term (i.e. all water-related risks), with an investigator(s)’ disciplinary background playing a role in limiting the scope of the study to selected water security concerns (Cook and Bakker, 2012). In addition, there have been few multiscale analyses of water security, and there currently is no systematic method to compare water security across scales. This paper offers an exploratory analysis of how a multiscale water security study could be conducted using the United States as a case study. To start, a brief review of water security evaluations is given as well as an overview of methods used in previous multiscale analyses. This is followed by a discussion of possible difficulties encountered when selecting an analysis scale, which could possibly impede a multiscale analysis. We then generate a water security composite indicator at two sub-national spatial scales to explore the compounded effect of multiple

risk types that contribute to water insecurity, as well as illustrate the spatial masking of water insecurity at higher levels of analysis.

### ***1.1. The contested nature of water security and spatial scale***

Whilst definitions of water security are contested, it is widely agreed that water security is a multi-dimensional construct. One way to convey the concept of water security is to create a composite indicator, simplifying the complexity to allow for easier benchmarking and comparisons. Several composite water security indicators have been created using a variety of methods. One common way to evaluate water security is in terms of the triple bottom line: people, the economy, and the environment (Sadoff et al., 2015), but very few previous indicators actually incorporate all three of these widely-accepted pillars of sustainability. In fact, amongst widely used indicators, only the Asian Development Bank (ADB) (2013; 2016) water security index touches on all three areas. Veettil and Mishra (2020) measure water security for the contiguous United States and Gain et al. (2016) measure water security globally, but both lack an economic and environmental risk component. Two key studies do not incorporate economic risk (Vörösmarty et al., 2010; Lautze and Manthrinthilake, 2012). Khan et al. (2020) incorporate all three risk types, yet, their environmental component only includes water quality indicators. It should also be noted that each composite indicator includes an additional component based on resource management (Vörösmarty et al., 2010; Lautze and Manthrinthilake, 2012; Gain et al., 2016; Khan et al., 2020).

The studies described above, as well as the majority of evaluations of water security in the literature, are applied to a single spatial scale of analysis. These include the household (Deitz and Meehan, 2019); local (Norman et al., 2013); county (Veettil and Mishra, 2020); urban (van Ginkel et al., 2018); country (Lautze and Manthrinthilake, 2012; ADB 2013, 2016); regional (Scott et al., 2013); the river basin (Petersen-Perlman et al., 2012); or global scale (Vörösmarty et al., 2010; Gain et al., 2016). The nation-state was found to be a routinely used scale in two different concept reviews of water security (Cook and Bakker, 2012; Gerlak et al., 2018), and there have been several country-level and multi-country reports generated (World Bank, 2017; World Bank, 2018). However, finer resolution studies have shown how water security can vary within a country (Vörösmarty et al., 2010; Gain et al., 2016). For example, in one report, Australia is listed as one of the most water secure regions in Southeast Asia (ADB, 2016). However, the map created in Vörösmarty et al. (2010) shows areas on the East coast of Australia that have both a high incidence of human and biodiversity threats to water security.

### ***1.2. Multiscale analyses***

Given the different and sometimes conflicting messages that are yielded by assessments at different spatial scales, there has been a call in the literature (Cook and Bakker, 2012; Wheeler and Gober, 2013) and across the policy discourse (GWSP, 2013) for the formation of multiscale water security analyses. For example, Cook and Bakker (2012, p. 99) go so far as to say that “a true picture of country water security requires assessment at multiple scales – from the local to the national – for both human and ecosystem needs.” Despite this need, there are hardly any multiscale studies in existence. The seminal assessment by Sadoff et al. (2015) for the Global Water Partnership and the OECD looked at water security across different scales, but did not conduct a tiered analysis of a single location. Young et al. (2019) conducted a diagnostic assessment of Pakistan’s water security and drew upon data across scales (primarily at the country level), but did not provide a systematic methodology to compare the overall water security between areas. Finally, the Asian Development Bank’s (ADB) studies (2013;

2016) do incorporate data on household and urban water security, but these indices are also not comparable, as they use different sub-indicators.

Even though multiscale assessments are not yet prevalent within the water security literature, there have been multiple analyses in other social science fields, such as vulnerability studies (McLaughlin and Cooper, 2010; Huynh and Stringer, 2018), adaptive capacity (Vincent, 2007; Marzi et al., 2018), and disaster resilience (Mitchem and Cutter, 2004; Cutter et al., 2016). In the field of disaster resilience, research has extensively focused on using geospatial techniques to explore how drivers of change vary by spatial scale (Cutter et al., 2016) and how vulnerability changes across scales (Mitchem and Cutter, 2004). Vulnerability studies and those looking at adaptive capacity have a similar purpose, with several studies using composite indicators to allow for multiscale comparisons of complex concepts (Vincent, 2007; McLaughlin and Cooper, 2010; Huynh and Stringer, 2018, Marzi et al., 2018).

The majority of studies employing composite indicators used different indicators at each scale of analysis, with one study going so far as to say that “it is not meaningful to transfer one index across scales” (Vincent, 2007, p. 22). Examples would be, in the case of Vincent (2007), the inclusion of an indicator on the ‘global trade balance’, which is not meaningful at the household level. In addition, we know that drivers of change may operate in different ways at different scales, such as urban disaster resilience being “driven by economic capital”, and rural resilience by “community capital” (Cutter et al., 2016). Nonetheless, whilst indicators at different scales need to be interpreted with caution, we argue that having broadly the same indicators at different scales is desirable, as using entirely different indicators makes interpretation extremely difficult.

Given that this topic has been explored more broadly in the social sciences, why do so few water security analyses account for multiple scales, and why do none allow for comparability across scales? To begin our exploration of these questions, we examine some of the challenges associated with the selection of scale for a water security assessment that may hinder a multiscale analysis.

### ***1.3. Four challenges of matching water security to spatial scale***

We have discussed how larger country or regional water security analyses can obscure spatial heterogeneity, meaning that hotspots of insecurity become obscured and distributional issues amongst different communities are invisible. Yet, there are tradeoffs when opting to use finer scales of analysis. Difficulties in selecting a scale of analysis are not solely an issue of water security studies, as spatial scaling issues have been discussed in the broader natural and social sciences (Gibson et al., 2000). We summarize the difficulties that arise from the selection of a spatial scale into four primary considerations that are further elaborated upon below: (1) the natural scale of the phenomenon, (2) the scale of data availability, (3) the discussion-making scale, and (4) precision versus accuracy.

Water security encompasses a range of phenomena in coupled human and natural systems. The conceptualization of these phenomena is subjective (Montello, 2001), but examining the literature, we observe recurrent units of assessment, which suggest that at least some of these phenomena have a ‘natural scale’. Examples include river basins as the natural scale at which to analyze and manage water resources (Garrrick and Hall, 2014), and the individual or household as being natural scales at which to analyze the human dimension of water security (Jepson et al., 2017). It may be argued that social processes are bound by political jurisdictions (Gibson et al., 2000), but this is challenged by increased layers of water governance (Swyngedouw et al., 2002). Water security is also affected by large scale processes such as climate change (Wheater and Gober, 2013). Outcomes in terms of people, the

economy, and the environment occur and are monitored across scales. As such, they can be measured differently or manipulated for a desired purpose. For example, if a dam may not have a desired economic outcome for a locale, one could change the scale of analysis and show that in terms of the river basin at large, it could be economically feasible (Reisner, 1986).

Obtaining data to describe and, where appropriate, quantify phenomena of interest is a perennial challenge in water security studies. This is one of the main reasons why multiscale studies are rare (Watson, 1978). Ideally, we would like to examine local heterogeneity, but data is seldom available. Thus, studies have tended to be dictated by the scale of data availability (Montello, 2001). One is often left with the choice of switching scales, limiting the analysis to match the available data, or manipulating the data for the desired scale. In terms of manipulation, data can either be downscaled or upscaled, but both come with flaws. For example, climate patterns can be downscaled to the community level, but each stepwise disaggregation carries increasing uncertainty (Wheater and Gober, 2013). Additionally, certain observed local phenomena may not be replicable across scales (Meentemeyer, 1989; Meyer et al., 1992). For example, a recent review of household water security found that current metrics have low replicability across cultures or regions (Jepson et al., 2017).

Water security studies often aim to inform decision making. Therefore, the evidence that is provided by a water security assessment should ideally map onto the scale of decision-making. Decisions include investments in both soft and hard infrastructures, which occur within the jurisdictions of government ministries or agencies, or sometimes within devolved administrations (Garrick and Hall, 2014). Decision making could involve changes to institutional governance and capacity that could occur at the local, river basin, national, or international levels (Grey et al., 2013). Water security decisions can also occur at an individual or household level. A household may have to weigh the options of where to obtain their drinking water or whether to incorporate drought-tolerant agriculture. Tradeoffs in resource allocation, e.g. between urban and agricultural areas, need to be mediated at a scale that incorporates all of the relevant actors (Swyngedouw et al., 2016).

The final consideration over-arches the phenomenon, data, and decision-making considerations: the tradeoff between precision versus accuracy. Given the tendency for larger levels of analyses to obscure finer variability, the assumption may be that the finer the resolution, the better. However, using a finer resolution or higher precision may, in fact, be detrimental (Goodchild, 1992). This is primarily due to the lack of accuracy that may come along with increased precision as one moves away from the scale of the phenomenon (Montello, 2001). For example, if looking at the individual or household, large scale global processes such as climate change would have to be significantly downscaled to fit this level of aggregation. Hydrological data would also have to be considerably downscaled. Ultimately, it may be more beneficial to study a coarser resolution or limit a case study to a single dimension, to preserve accuracy. However, this may also conflict with the scale of decision making and be limited by the scale of data availability.

Each of these considerations is encountered when selecting a scale of analysis for any water security study. The considerations raised in regarding data availability and precision versus accuracy are especially evident within a multiscale analysis. Also, choosing which considerations to prioritize may result in trade-offs, such as prioritizing the decision making scale, even if this involves disaggregating the natural scale of the phenomenon – aggregation is less problematic. Given these issues, how does one systematically conduct a multiscale water security analysis that is comparable across scales?

In this study, we explore the feasibility of conducting a water security analysis across scales by creating a composite water security indicator, only focusing on indicators available across all scales of analysis. The water security index is based on ten sub-indicators comprised of both performance and outcome related data. Due to data availability and a consistent spatial structure of jurisdictions (national, state, county), we use the United States of America (USA) as our case study. The indicators are amassed for the USA and its constituent states and counties. The final composite index is only generated at the county and state scales and is not replicable across other countries due to data availability. Thus, it does not allow for cross-country comparisons. However, by systematically evaluating water insecurity across two sub-national scales, it does allow for a tiered analysis of water security across administrative boundaries. Even though the exact indicators may be subject to data availability, the overall methodology can be adapted to a given nation. The index could also be reconfigured and tailored to meet desired objectives (i.e. changing the weight scheme). Therefore, this composite indicator will be useful for policymakers as a way to focus resources on areas of water insecurity.

## 2. Methods

The first step in the methodology is to describe the underlying water security framing that serves as the basis for the composite indicator. We then discuss our choice of case study. The framing and decision of scale lead to the identification of ten separate indicators focused on system performance and outcomes. These indicators are amassed for the USA and its constituent states and counties. We then discuss how these indicators were normalized, aggregated, and weighted to create the overall composite index.

### 2.1. Conceptual framing

The conceptual framing is one of the most critical factors in the creation of a composite indicator (OECD et al., 2008). We chose to focus on a multi-dimensional framing of water security that was created by Doeffinger et al. (2020), which aligns with the broad definition of water security given by Grey et al. (2013). The framing consists of seven categories of information that are vital to the understanding and evaluation of water security: “(1) drivers, (2) historical and cultural context, (3) the water resource system, (4) system performance, (5) outcomes, (6) actions, and (7) trends” (Doeffinger et al., 2020, p.5). Of these seven categories, the water security index created herein is comprised of only two: system performance and outcomes. These two categories were selected as they indicate the status of water security. Whereas, the other categories either indicate how water security may change in the future, provide context, detail the current status of the resource system, or examine potential intervention decisions (Doeffinger et al., 2020).

The system performance indicators speak to whether water is being managed constructively and refer to resource usage and the infrastructure and institutions that are currently in place (Doeffinger et al., 2020). In terms of water resources, indicators could include sustainability of use, overall quality, productivity, and efficiency. Infrastructure and institutional performance could include the deterioration of infrastructure as well as future needs. It also entails understanding the current institutional capacity and effectiveness.

Outcomes relate whether water-related risks have been mitigated or if water security has been achieved. Here, outcomes keep with the triple bottom line definition of sustainability and focus on people, the economy, and the environment (Doeffinger et al., 2020). Outcomes in terms of people primarily revolve around their experience with water services as well as impacts in regards to water-

related shocks. The economy is also susceptible to water-related shocks, and there can also be economic losses due to issues with poor services. Finally, the environment can be affected in terms of single species deterioration or overall ecosystem loss.

## **2.2. Case study selection**

The USA is used as a case study to illustrate the spatial variability of water security. This is done for two primary reasons, first, due to the availability and access to data across reporting scales. Second, the USA is a vast country with known spatial heterogeneity for several water security indicators. When looking at the country as a whole, it does not appear to exhibit any acute signs of water insecurity, such as a lack of access to improved drinking water sources (WHO/UNICEF, 2019), high vales of water stress (FAO Aquastat, 2019), or a national issue with pollution (Sadoff et al., 2015). However, the country as a whole is subject to frequent flood events that are both costly in terms of dollars and loss of life (EM-DAT, 2019). There is also evidence of specific water security challenges: rising seas in Miami (Wdowinski et al., 2016), water stress in the Southwest (Wada and Bierkens, 2014), and groundwater depletion across the Great Plains (Steward and Allen, 2016). These subnational issues are obscured when conducting a country analysis.

There are many scales available for analysis in the USA, with system performance and outcomes typically reported based on administrative boundaries. The main administrative boundaries used in the USA are as follows (ordered from coarsest to finest resolution): country, states, counties (including parishes and independent cities in Virginia), census tracts, and households. The institutional and infrastructure performance data are primarily aggregated and reported at the state and county levels. Even though hydrological data is situated to the river basin (Garrick and Hall, 2014), in the USA, data on water withdrawals are reported at the county level, and data on quality is reported at the county and state level. Outcomes can be reported across all of the administrative boundaries listed above. Ultimately, we chose to assemble indicators at the country, state, and county levels as they are representative across the majority of indicator types and allow for a tiered analysis.

## **2.3. Indicator selection**

The data selection was driven by the need to have similar indicators across both the county and state scales. The study was limited by the county scale, with more data being available at the state level. All data for the country, state, and county scales are from the same source, except for impaired stream/river length. All data, except for the number of aquatic species of conservation concern, are publicly available, and references can be found in Table 1. The data fall between 2004 – 2018, with the most recent year of data availability being used for each indicator. However, flood deaths, flood damages, and drought damages are summed over a 10 year period between 2008-2018 in order to capture significant water-related shocks across the USA. Finally, the number of drought deaths is not included within this index as there were none reported within the USA during the time period. For a full explanation of indicator calculations, scaling, and their individual limitations, please see the Supplementary Material.

**Table 1.** Indicators and their sources

Dimension	Indicator	Unit	Timeframe	Source
<b>Systems Performance</b>				
Sustainability of Usage	Water Stress	%	2014	WRI Aqueduct, 2019
Water Quality	Impaired Stream/River Length*	%	2004, 2006, 2008, 2010	EPA, 2013
Productivity	Agricultural Water Productivity	2019 USD/m <sup>3</sup>	2015	Dieter et al., 2018a; BEA, 2019; USDA, 2019a
Infrastructure	Wastewater Investment Need	2019 USD	2012	EPA, 2012a
Institutions	CWS Not in Compliance	%	2018	EPA, 2020b
<b>Outcomes</b>				
People				
Service	Lacking Complete Plumbing	%	2017	ACS, 2020
Floods	Flood Deaths	-	2008 - 2018	NOAA, 2020
Economy				
Floods	Flood Damages	2019 USD	2008 - 2018	NOAA, 2020
Droughts	Drought Damages	2019 USD	2008 - 2018	USDA RMA, 2019
Environment				
Biodiversity	Aquatic Species of Conservation Concern	-	2019	NatureServe, 2019a

\* State data is from EPA, 2020a

Each of the ten sub-indicators gives an indication of the current status of water security, and when combined, offers a multi-dimensional assessment of the water security of a given area, as compared to more narrow assessments of water security in the US, such as those focusing on scarcity (Veettil and Mishra, 2020) or access to services (Deitz and Meehan, 2019). Each of the performance indicators gives insight into issues that could hamper the achievement of water security. High stress corresponds to water insecurity, as it indicates an area is not using its resources sustainably. Poor quality is an issue of insecurity due to potential adverse health concerns, but also due to its ability to limit the quantity of water available for specific uses, i.e. drinking water. Low agricultural productivity shows that there are inefficiencies in the agricultural use of water. Poor performing institutions can lead to water insecurity in many ways, but in this case, failure to meet a standard would indicate a higher likelihood of drinking water contamination. In addition, each of the five performance indicators can impact overall water security outcomes. For example, poor water quality could contribute to a loss in biodiversity. Finally, high values in each of the five outcome indicators correspond to a higher incidence of water insecurity.

#### 2.4. Summary statistics

Tables 2 and 3 illustrate the summary statistics at the county and state levels, respectively. There are a total of 3,142 counties within the US. There are fifty states, plus the District of Columbia. Missing data is primarily a concern at the county level, with large gaps in the number of aquatic species at risk. From Table 2, we see that the county indicators all have a tendency to skew to the right, some more prominently than others. From Table 3, we see the same skew pattern, except for the impaired stream/river length. For nine of the ten indicators, a higher value indicates the potential for higher water insecurity, although a lower value of agriculture water productivity would be cause for concern.

**Table 2.** County Summary Statistics

Indicator	No. of Counties	Min	Max	Mean	Median	SD
Water Stress (%)	3,137	0	378.37	23.13	14.52	28.09
Impaired Stream/River Length (%)	3,139	0	98.50	10.68	6.29	14.86
Agricultural Water Productivity (USD/m <sup>3</sup> )	2,834	0	176.86	1.15	0.19	5.77
Wastewater Need (USD)	2,483	3.54E+04	9.21E+09	1.20E+08	1.18E+07	5.23E+08
CWS Not in Compliance (%)	3,129	0	100	32.87	28.13	27.86
Lacking Complete Plumbing (%)	3,142	0	37.31	0.64	0.38	1.45
Flood Deaths	3,103	0	61	0.46	0	1.83
Flood Damages (USD)	3,103	0	1.53E+10	4.31E+07	6.92E+05	5.31E+08
Drought Damages (USD)	2,666	519.98	4.30E+08	1.73E+07	6.54E+06	3.02E+07
Aquatic Species of Conservation Concern	1,966	1	36	3.95	2	4.29

**Table 3.** State Summary Statistics

Indicator	No. of States	Min	Max	Mean	Median	SD
Water Stress (%)	50	3.01	88.80	23.20	18.02	18.64
Impaired Stream/River Length (%)	51	3.77	100.00	59.11	61.10	25.87
Agricultural Water Productivity (USD/m <sup>3</sup> )	51	0	1.61	0.52	0.35	0.45
Wastewater Need (USD)	51	1.01E+08	3.49E+10	5.83E+09	3.41E+09	7.14E+09
CWS Not in Compliance (%)	51	3.82	73.93	32.94	30.91	18.12
Lacking Complete Plumbing (%)	51	0.24	3.96	0.48	0.38	0.51
Flood Deaths (#)	51	0	278	27.29	17	41.03
Flood Damages (USD)	51	0	6.10E+10	2.62E+09	2.45E+08	9.19E+09
Drought Damages (USD)	51	0	9.29E+09	9.02E+08	2.60E+08	1.59E+09
Aquatic Species of Conservation Concern (#)	51	4	692	153.12	62	187.96

When looking at the correlations between indicators across counties, seen in Table 4, the majority of the correlations shown are weak (having a value less than 0.4). However, we do see a high correlation between the number of flood deaths and the total flood damages and high water stress and drought damages, which is to be expected.

**Table 4.** Correlation between indicators at the County level

	Stress	Impaired Rivers	Ag Productivity	Wastewater Needs	CWS No Compliance	Lack of Plumbing	Flood Deaths	Flood Damages	Drought Damages	Aquatic at Risk
Stress	1									
Impaired Rivers	-0.09*	1								
Ag Productivity	-0.00	0.05*	1							
Wastewater Needs	0.13*	0.12*	0.12*	1						
CWS No Compliance	0.04*	0.05*	-0.01	0.04	1					
Lack of Plumbing	-0.02	-0.07*	-0.01	-0.06*	0.15*	1				
Flood Deaths	0.04*	0.03	0.02	0.24*	0.03	0.01	1			
Flood Damages	0.01	0.04*	0.00	0.09*	0.01	-0.01	0.46*	1		
Drought Damages	0.31*	-0.09*	-0.06*	-0.06*	0.09*	0.00	-0.05*	-0.02	1	
Aquatic at Risk	0.05*	-0.03	0.04	0.07*	-0.01	-0.03	0.07*	-0.02	-0.05*	1

\*p < 0.05

Correlations at the state level are similar, as seen in Table 5. Although some have a higher value, these differences may simply be due to the smaller sample size. Again, we find the highest correlation between the number of flood deaths and the total amount of flood damages. There is also a high correlation between drought damages and both the number of flood deaths and total flood damages. This could primarily be driven by Texas, which experienced the highest drought losses, greatest flood damages, and the most flood deaths during the time period. Missouri was also susceptible to flooding and recorded high drought losses.

**Table 5.** Correlation between indicators at the State level

	Stress	Impaired Rivers	Ag Productivity	Wastewater Needs	CWS No Compliance	Lack of Plumbing	Flood Deaths	Flood Damages	Drought Damages	Aquatic at Risk
Stress	1									
Impaired Rivers	0.04	1								
Ag Productivity	-0.02	0.27	1							
Wastewater Needs	0.20	0.10	0.26	1						
CWS No Compliance	0.05	0.05	-0.24	-0.01	1					
Lack of Plumbing	-0.04	0.04	-0.25	-0.16	0.33*	1				
Flood Deaths	0.22	-0.12	-0.07	0.36*	0.08	-0.04	1			
Flood Damages	0.15	-0.01	0.10	0.26	0.13	-0.04	0.81*	1		
Drought Damages	0.18	0.00	-0.03	0.12	-0.08	-0.10	0.70*	0.67*	1	
Aquatic at Risk	0.10	-0.05	0.19	0.25	-0.11	-0.13	0.42*	0.20	0.15	1

\*p &lt; 0.05

## 2.5. Index creation

Since there are multiple unit types for the ten indicators, the data was normalized before aggregation. There are various ways to normalize indicators to generate a composite index, including ranking, z-scores, scaling to have the same minimum and maximum, and categorical (Jacobs et al., 2004; OECD et al., 2008). Several of the indicators have large outliers (e.g. waste water needs), whereas others tend to cluster around a single value (e.g. lacking complete plumbing), making it difficult to choose an ideal normalization method. There are also additional considerations, such as the ability to track progress through time, which can be obscured by using categorical methods (OECD, 2008). Ultimately, we chose to use a ranking-based normalization approach, and each indicator at both the state and county level was ranked. Values are ranked from lowest to highest, with the highest value receiving the highest rank value. Therefore, when aggregated, higher values will indicate areas of water insecurity. However, for agricultural water productivity, values were ranked from highest to lowest, with the lowest value getting the highest rank value since lower productivity would be more of a security concern. Given that there are missing data for each indicator at the county level, not every indicator is ranked on a scale of 1 – 3,142. In addition, some indicators have multiple counties and or states with the same value, and therefore they received an equal rank value. This is especially true for the number of aquatic species of conservation concern and the number of flood deaths. Values that were reported as zero across all indicators were ranked as zero since this would represent zero insecurity.

For this analysis, indicators are given equal weights. This means that equal importance is assigned to each indicator. As preferences can change across a range of stakeholders, this weighting essentially creates a base index that can be customized in the future to account for a given area's preferences. An alternative method that could have been adopted is based on statistical analyses such as Principal Component Analysis (PCA) or Factor Analysis (FA). Jacobs et al. (2004) highlight values greater than  $\pm 0.4$  as having high correlations. Thus, a PCA was not implemented as the fairly low correlations at the county scale between most variables ( $< 0.4$ ) meant that PCA would not be particularly effective at dimension reduction. There are stronger correlations found at the state level, but we chose to remain consistent in our methodology across scales. Overall, the highest correlation at both scales occurs between flood deaths and flood damages, which is to be expected. Nonetheless, we are interested in the impacts of floods on both people and the economy, so they are left equally weighted.

A linear aggregation methodology (the sum of normalized indicators) is employed. This assumes constant compensability, or that a decrease in one indicator can be accounted for by the increase in another (Information Resources Management Association, 2018). This essentially says that a loss of biodiversity can be made up for by good institutional performance. This is not an ideal aggregation method. Yet, in this first attempt at generating a water security index across scales, we are primarily interested in seeing the overall compounding effect of sub-indicators. Again, this is a generic

aggregation method that could easily be updated to reflect an area's desired objectives, i.e. a primary focus on the environment or sustainable water usage.

To check the robustness of the overall index, two of the underlying parameters were varied to perform a sensitivity analysis: the normalization method and the weighting scheme. The rank-based normalization method was chosen for its flexibility in dealing with the underlying data discrepancies (i.e. missing data, outliers, and clustering around a single value). However, we test the variability in the final index value at the state level as compared to three other normalization methods: min-max, z-score, and quantile based categorization. In addition, the ranked-based normalized index created using equal weights (WSrew) is compared with an additional weighting scheme. The hierarchical weighting scheme (WSrhw) is generated by the authors and employs the same ranking-based normalization method. It is similar to a weighting scheme employed by Gain et al. (2016) by placing a larger emphasis on water stress and access to water services. In addition, the weighting scheme takes into account the correlation between flood deaths and flood damages, with each given lowered weights, as well as giving less weight to indicators with large data gaps (i.e. drought damages and aquatic species). The weights can be viewed in Table 6. As there were no alternative datasets available for the majority of the dimensions in Table 1 (for a more thorough description, see the Supplementary material), we were not able to assess the sensitivity to indicator selection. We also did not assess the uncertainty associated with the aggregation method, as 1) linear aggregation maximizes the ease of interpreting the results and 2) most similar water security indices use a linear aggregation method (Vörösmarty et al., 2010; Lautze and Manthrinthilake, 2012; ADB, 2013; ADB, 2016; Khan et al., 2020).

Table 6. Two Separate Weighting Schemes			
Dimension	Indicator	WSrew	WSrhw
<b>Systems Performance</b>			<b>0.5</b>
Sustainability of Usage	Water Stress	1	0.4
Water Quality	Impaired Stream/River Length	1	0.2
Productivity	Agricultural Water Productivity	1	0.1
Infrastructure	Wastewater Investment Need	1	0.1
Institutions	CWS Not in Compliance	1	0.2
<b>Outcomes</b>			<b>0.5</b>
People			
Service	Lacking Complete Plumbing	1	0.6
Floods	Flood Deaths	1	0.1
Economy			
Floods	Flood Damages	1	0.1
Droughts	Drought Damages	1	0.1
Environment			
Biodiversity	Aquatic Species of Conservation Concern	1	0.1

## 2.6. Mapping of results

Choropleth maps are employed to show the variation in sub-indicators as well as the overall water security index. All maps were made using the US Census (2019) boundary shapefiles. Maps for only two out of the ten sub-indicators are presented in Section 3. These two sub-indicators were chosen as maps for each of these indicators are not readily accessible, and they serve to show how the variation in sub-indicators can inform the overall index as well as illustrate some of the underlying data issues (i.e. missing data). Maps of the additional eight sub-indicators can be found in the Supplementary Material.

In terms of missing data and the index generation, only counties with at least nine indicators are mapped and presented in the results section. Thus, only 2,526 counties are mapped or 80% of all counties. At the state level, Hawaii is the only state with a missing value (water stress), and it was included in the final aggregation. This is noted, as only the contiguous states are shown in the results section. For a complete list of data values for states, along with their ranks and final total rank value, please see the Supplementary Material. Finally, when looking at the overall results for the composite indicator, the aggregated values were placed in five separate brackets or quintiles, with an equal number of counties or states in each bracket. This was done to allow for comparisons.

Finally, the difference between the composite indicator based on equal weighting (WS<sub>rew</sub>) and the hierarchical weighting (WS<sub>rh</sub>) is mapped to visualize sensitivity. The composite indicator for each weighting scheme, WS<sub>rew</sub> and WS<sub>rh</sub>, are normalized to a scale of 0 – 1 before calculating the difference.

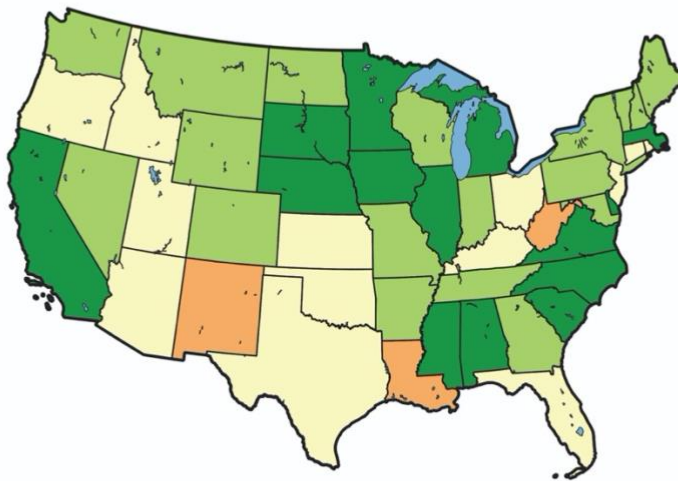
### **3. Results**

#### ***3.1. Mapping sub-indicators***

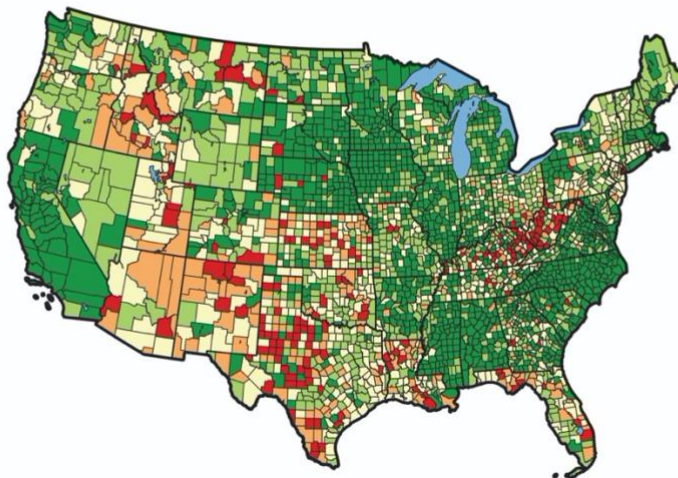
These maps are used to illustrate the masking of heterogeneity at higher spatial scales. Figure 1 shows the percentage of Community Water System (CWS) facilities not in compliance with the Safe Drinking Water Act (SDWA) and represents institutional performance. This indicator is mapped across three scales. In Figure 1a), we see that the USA as a whole does not show a high level of violations. In fact, only 31% of CWS facilities in the USA were violators in 2018. When looking at the state level, Figure 1b), we see some variation. Here, three states show larger values (60%-80%) of noncompliance, and thirteen states show reason for concern, with noncompliance falling between 40% to 60%. However, the vast majority of states are in the same bracket as the USA (20%-40%) or lower. It's not until we look at the counties in Figure 1c) that we begin to see finer variation. There are areas now within the highest category (80%-100%), with large concentrations of counties located in the Ohio River Valley, several South Central states, and a few North Central states. We also see counties in California, the Northeast, as well as counties around the Great Lakes with low levels of violations. Also, even though several states in the Southeastern USA show a 0-20% rate of noncompliance, we do see several counties in this area that have a noncompliance rate of between 80%-100%. This could be due to some counties having a small number of CWS facilities, with the majority having a violation.



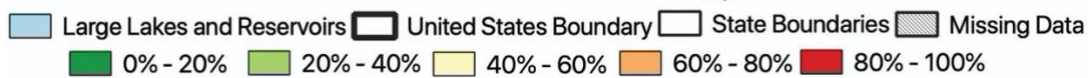
a)



b)



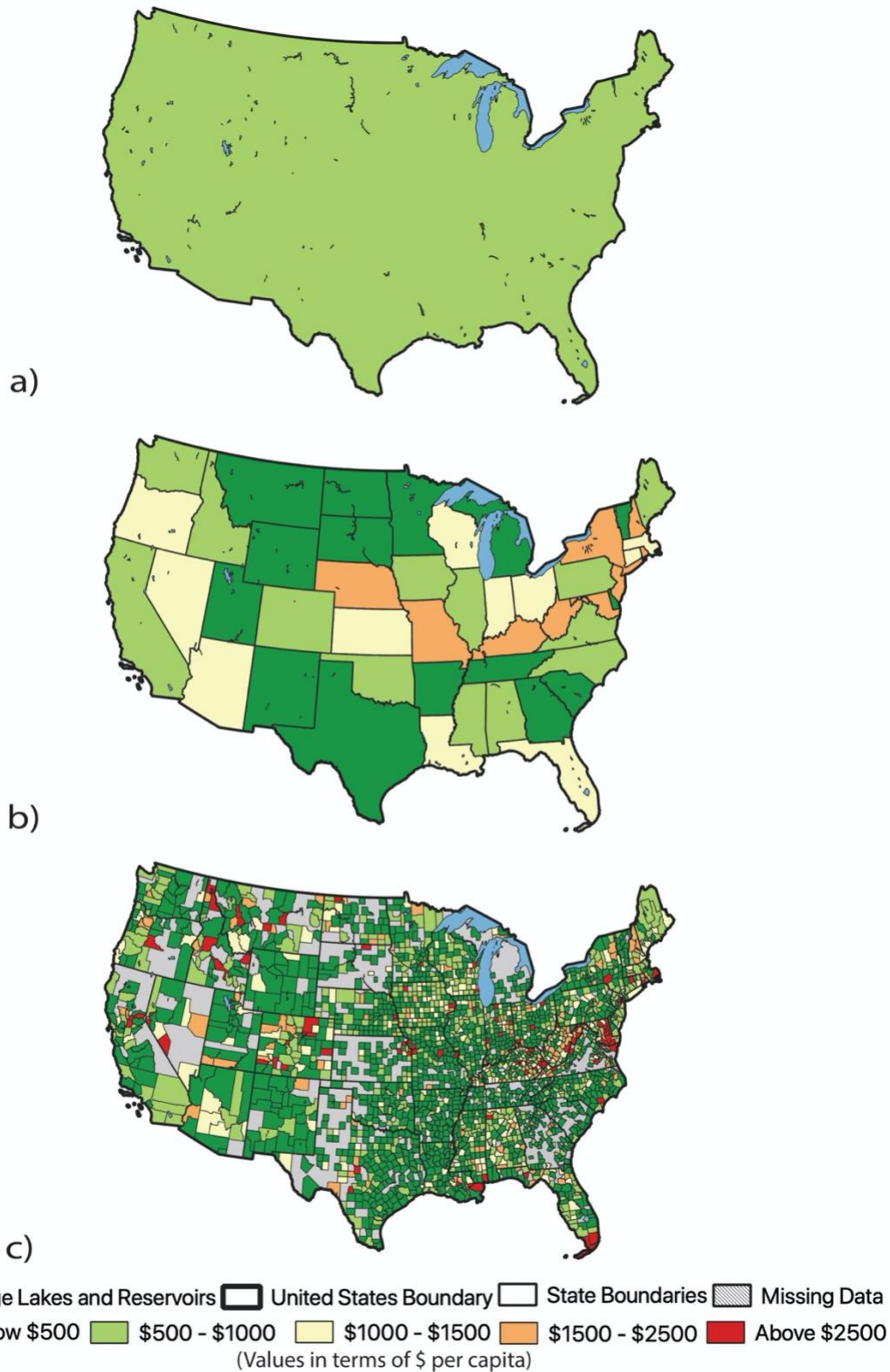
c)



**Figure 1:** Institutional performance in terms of the percentage of CWS facilities not in compliance with the SDWA (EPA, 2020b). This figure shows results across three scales: a) country, b) states, and c) counties.

Figure 2 shows the dollar amount of wastewater needs across three scales: the country, states, and counties. For this indicator, each stepwise increase in scale is an aggregation of a smaller scale. This indicator is a nominal value. Thus, to make the indicator comparable across these scales, the data is reported in terms of needs per capita. This shows that even though data is available across scales, the comparability of nominal values may not necessarily be meaningful until put in context.

As far as spatial heterogeneity, we see in Figure 2a) that the USA has wastewater needs between 500 USD and 1,000 USD per capita. This is low when compared to values seen at the two other scales. For example, in Figure 2b), we see that nine states have a need of between 1,500 USD and 2,000 USD per capita. We can also see that the majority of states that have the highest needs often border another state with high needs as well. Finally, in Figure 2c), we begin to pick up on more spatial heterogeneity. However, we also see that there are a large number of counties with missing data. Several large swaths of missing data are in states such as Texas and the North and South Dakota that ultimately show low wastewater needs overall. These values could be uncharacteristically low due to missing data. Also, we see several states such as New York that have the majority of counties with a low need per capita, but ultimately show higher levels of need at the state level. These maps begin to show some of the interesting cross-scale dynamics.

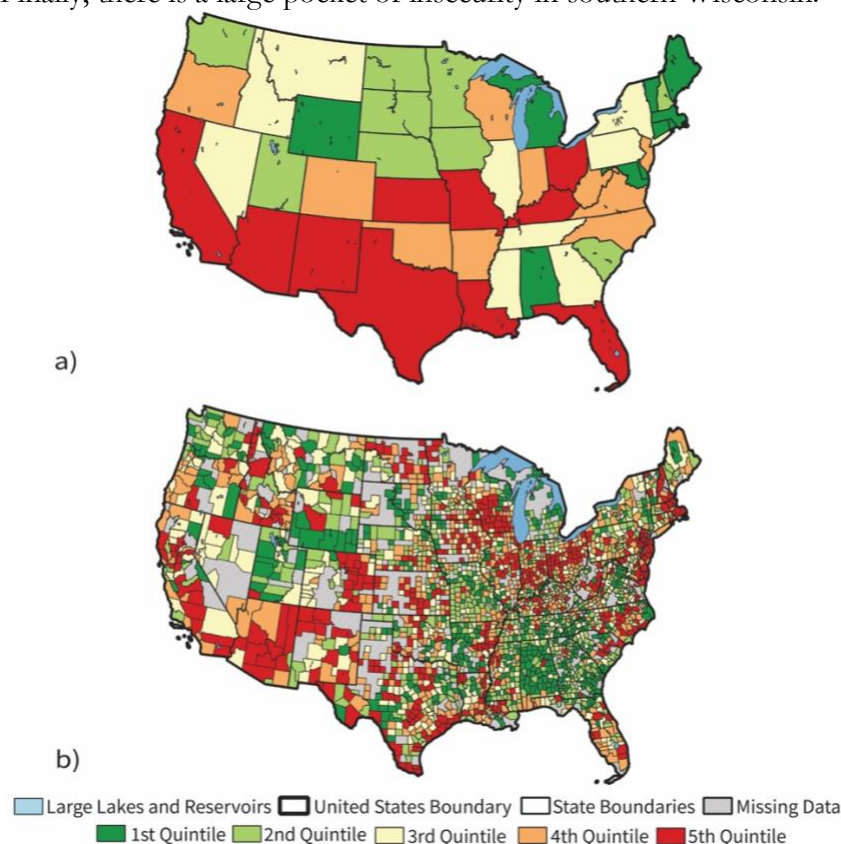


**Figure 2:** Infrastructure performance in terms of wastewater needs per capita (EPA, 2012a). This figure shows results across three scales: a) country, b) states, and c) counties. These values are in terms of USD (\$) per capita to aid in cross scale comparisons. Population values are based on 5-year population estimates for 2017 (ACS, 2020).

### 3.2. Composite Indicator

The overall composite indicator for both the state and county scales is seen in Figure 3. There is an equal number in each of the five brackets for both scales. Thus, the insecurity level is based on a given state or county's performance in regard to one another. The 1<sup>st</sup> quintile corresponds to low water insecurity, whereas the 5<sup>th</sup> quintile would indicate areas of high insecurity. In Figure 3a), we can start to recognize patterns and group areas based on their insecurity levels. The Northeast appears to be relatively water secure. There is also a pocket of low insecurity in the North Central states. There is a group of high insecurity states along the southern border. This could be split into two areas: the Southwest and the Gulf Coast. There is also a pocket of insecurity along the Ohio and Mississippi Rivers.

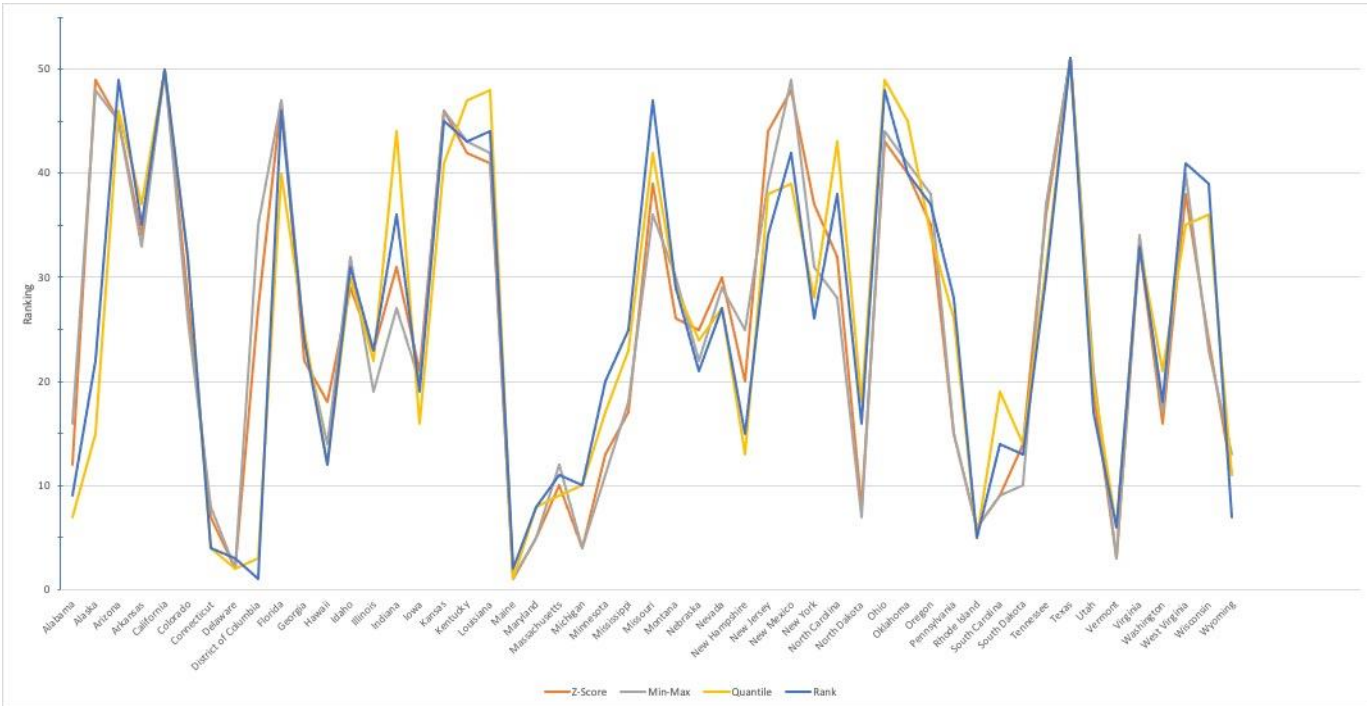
When looking at the water security index values at the county level, Figure 3b), we see some similarities, but also differences. The Southeast and the Southwest of the USA both seem to have areas of high insecurity at the county and state scales. One large difference is seen when comparing several states that are described as having high insecurity, but have hardly any counties within this bracket, such as Missouri. Also, there are several states listed as having low insecurity that have many counties with above average or high insecurity. This can be seen primarily in the Northeast of the USA. There are higher insecurity levels seen in counties along the Mississippi River. However, the insecurity that was seen amongst the Ohio River states actually shows specific clusters of insecurity within the broader river basin, in areas such as North Central Ohio and the Appalachian region of West Virginia. Finally, there is a large pocket of insecurity in southern Wisconsin.



**Figure 3:** Water security composite indicator at two scales: a) the state and b) the county.

### 3.3. Sensitivity results

Two primary causes for uncertainty within our water security indicator were assessed. First, we look at the normalization method used. Figure 4 shows the variance that occurs in the overall ranking of the water security composite index at the state level based on four different normalization methods. One can see that several of the states' final ranked-value of insecurity are quite different, such as Alaska. Whilst, there is more convergence on the extreme values, e.g. Arizona, California, and Texas. This indicates the most insecure states consistently score poorly across normalization methods.



**Figure 4:** Variance in the ranking of state insecurity caused by differences in normalization method

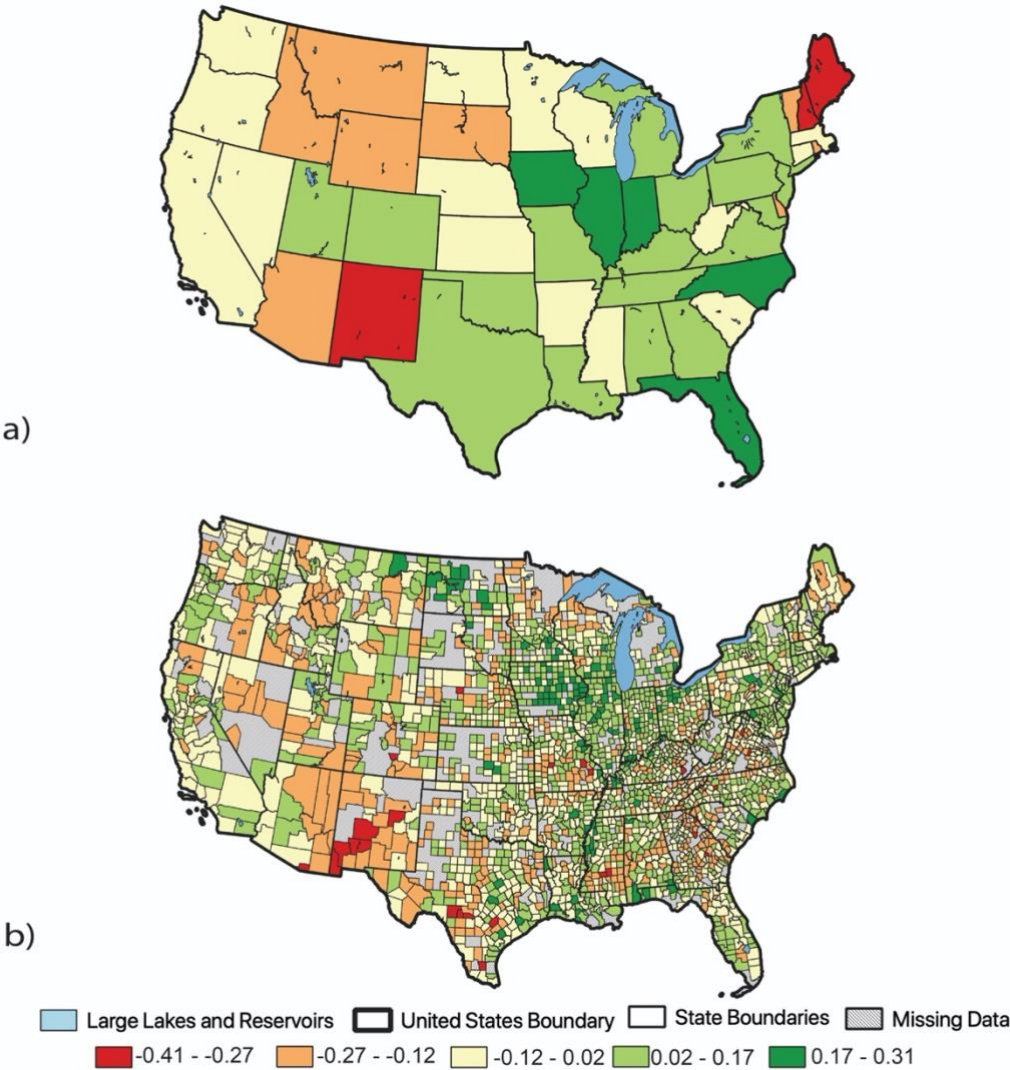
Table 7 details the summary of the differences between the composite index state rankings. Based on these results, the z-score and the min-max normalization methods produce relatively similar results, and likewise, the ranking and quantile categorization methods are also related. However, when comparing ranking to either the min-max or z-score normalization methods, the standard deviations are quite large. This could be due to the discrepancies in the underlying data discussed in Section 2.5.

**Table 7.** Differences in composite index rankings based on normalization method

	Rank-Zscore	Rank-MinMax	Rank-Quantile	Zscore-MinMax	Zscore-Quantile	MinMax-Quantile
Minimum	-27	-34	-8	-8	-13	-17
Maximum	15	16	7	6	34	33
Standard Deviation	7.36	8.17	3.13	2.62	8.09	8.98

Figure 5 illustrates sensitivity within the composite indicator to the chosen weighting scheme. The ranked-based, equal weight water security index (WS<sub>rew</sub>) is compared to a hierarchical weighting (WS<sub>rh</sub>) scheme. States and counties that are red and orange became more insecure due to the change in weighting, whereas green states and counties performed better. Given the increased importance given to access to complete plumbing, it is of no surprise that the largest negative changes are found

in areas with low access to complete plumbing (for comparison see Figure S4 in the Supplementary Material). In addition, flood damages and deaths were given low weights due to their correlation, and this contributes to the states along the Gulf and southern Atlantic Coasts actually performing better (i.e. more water secure).



**Figure 5:** Difference between  $WS_{rew} - WS_{rhr}$  at two scales: a) the state and b) the county.

## 4. Discussion

### 4.1. Scaling

Figures 1 through 3 demonstrate how the state and national scales can obscure finer level details and mistype areas as water secure. Several sub-indicators, such as water stress, had extensive spatial heterogeneity (seen in Figure S1 in the Supplementary Material). When looking at the USA as a whole, several water stressed regions are obscured. This was as expected based on previous global studies (Wada and Bierkens, 2014). However, this was not true for all indicators. For example, access to complete plumbing (seen in Figure S4 in the Supplementary Material) had little variation. Though

these findings may be expected, the analysis itself is useful as it illustrates challenges encountered during a multiscale analysis as well as illustrates the need of such studies.

Throughout the analysis, we encountered the four challenges described in Section 1.2, which resulted in three primary tradeoffs between matching water security to the spatial scales of analysis: (1) tiered index versus comprehensive analysis, (2) scale of analysis versus the natural scale of the phenomenon, and (3) multiscale analysis versus data availability. Since we chose to conduct a tiered multiscale analysis, we decided to forgo a full multi-dimensional analysis of water security by only focusing on system performance and outcomes (i.e. we did not consider drivers of change). This limited the overall scope of the study and narrowed the scale of analysis as system performance and outcomes are typically measured at a governmental scale. However, this could be seen as beneficial as the index is now tied directly to potential decision-making scales (e.g. state and county). The selection of administrative boundaries as the scale of analysis then resulted in a tradeoff as we had to sacrifice the natural scale of hydrological indicators, such as water stress. This resulted in a loss of accuracy for certain indicators (e.g. water stress and water quality), along with an increase in the accuracy of others (i.e. institutions). Finally, we encountered a tradeoff between data availability across scales, as useful data were excluded due to their unavailability at the finest resolution (the county). Even though we experienced multiple tradeoffs throughout the analysis, we have demonstrated that a multiscale analysis is feasible.

Based on the results, we recommend a continual assessment of water security at the finest scale available (in this case, the county) to account for spatial heterogeneity and track changes in water insecurity. Yet, we believe a multiscale water security analysis would also be advantageous when allocating resources to combat insecurity, especially in countries like the USA that have multiple levels of government. As of now, there is no way to compare the water insecurity of a county in Ohio to a county in West Virginia, or to compare metrics at the county level to those used at the state. So, a tiered multiscale assessment would allow for tracking and benchmarking of water security by producing a standardized indicator set, and in this case, a composite index. This would enhance the appropriation of federal funds to the most at risk states and or counties.

#### ***4.2. Usefulness of the composite indicator***

The creation of an index allows us to systematically assess water security across ten sub-indicators at two scales: the county and the state. It is, therefore, novel in its scope as well as its intent. A recent publication does measure water security at the county level for the contiguous United States, but focuses solely on scarcity indicators and indices (Veettil and Mishra, 2020). The only other water security index that is deemed comprehensive, in terms of the dimensions it incorporates (e.g. system performance and outcomes), is the ADB (2013; 2016) water security index. However, the USA is not included in this analysis, so a comprehensive water security indicator for the country is lacking. When compared to looking at each individual sub-indicator, our composite water security index allows one to get a better picture of the compounding effects of multiple water-related issues. It is also the first water security index that allows for a classification of water security that can be compared across scales.

Even though the USA as a whole may be seen as water secure, there are actually several areas of high water insecurity throughout the country. The arid Southwest of the country and several coastal states are unsurprisingly ranked highest in terms of water insecurity. What is interesting is the pocket of water insecurity found among the Ohio River Basin, as well as a pocket of water insecurity in Southern

Wisconsin. The Ohio River Basin has had a long history of water quality issues, albeit it has improved since the 1970s (White et al., 2005). Yet, there are still numerous chemical manufacturers located along its tributaries, and many cities along the river still use combined sewage overflow systems (White et al., 2005). The area is also home to rich farmland, but has low agricultural water productivity (See Figures S.3 in the Supplementary Material). In addition, this basin is prone to flooding, but areas in the basin have also experienced mild to moderate droughts over the last decade (USDAM, 2020). If taken as separate issues, the counties within the Ohio River basin may not rank as high priorities when compared to the rest of the country. However, by combining these water-related risks, pockets of insecurity are found that would otherwise be obscured. So, we find not only that a subnational assessment would be advantageous as critical areas of insecurity could be deemed water secure, but demonstrate the importance of taking a combined multi-risk perspective when assessing water security to gather a more realistic picture of water-related risk.

#### **4.3. Limitations of the composite indicator**

The quality and quantity of data is a principal limiting factor in the generation of the composite index. Each of the ten sub-indicators employed in this study has its drawbacks. Several of these issues can be improved in the future as new data becomes available. Key indicators could be the affordability and reliability of water services. The American Household Survey (AHS) does ask a question regarding the stoppage of water usage by households, and this has been used as an indicator of service reliability (Pierce and Jimenez, 2015). This survey is aggregated to the national level, but disaggregated data for each state and county are not currently available (AHS, 2017). Additional water quality and environmental outcome indicators, as well as infrastructure and institutional performance indicators, would also be advantageous. In addition, more attention could be paid to the cross-scale dynamics between indicators, which this study assumes to vary linearly. This is especially true for indicators that were disaggregated or aggregated to a new scale, i.e. water stress.

By opting to use similar methods across scales, we allowed for a direct comparison of the composite across scales. However, choosing to use similar methods came with a tradeoff of no longer having an equally robust composite indicator at each scale. As seen in Table 4 and 5, the indicators at the state level have high correlation values, indicating that a PCA analysis would be an appropriate approach at this scale.

There is also the question of the overall accuracy of the composite indicator due to the inherent uncertainty that comes with its creation (Saisana et al., 2005). This includes the following areas of uncertainty: conceptual framing, indicator selection, dealing with missing data, normalization, weighting, and aggregation. Essentially, each of these steps in the composite indicator creation introduces uncertainty. We performed a simple sensitivity analysis on the composite indicator, only focusing on the normalization method and comparing the composite indicator to one additional weighting scheme. We found a high discrepancy between the ranking normalization method and min-max or z-score based methods. We still chose to use a ranking based approach as it accounted for underlying discrepancies in our data (e.g. having both outliers and clustering). We also chose to use an equal weighting scheme, for the sake of parsimony and ease of interpretation. However, we demonstrate the sensitivity of the composite to the chosen weighting.

## **5. Conclusions**

Spatial scaling of water security studies will always present a challenge to both researchers and policymakers. The four considerations laid out in Section 1.2 occur during the selection of scale in any water security analysis, but can be exacerbated when conducting a multiscale analysis. Even though multiscale analysis brings more insight into phenomena of interest and can inform decision making at multiple scales, it includes great, and sometimes insurmountable, challenges regarding data availability. There will also be an increased interest in questions of precision versus accuracy since the scales of analysis will unlikely map onto the scales of the phenomena across all scales. Therefore, it may be more productive to focus on specific dimensions of water security. This narrowing of the concept can simplify the complexity of water security to fit the multiscale study to the desired phenomenon. For example, by focusing on water security outcomes, which are typically measured based on administrative boundaries, we can capture several indicators that are naturally measured in a nested structure.

Regardless of these issues, we do find that a multiscale analysis is beneficial as we unearth spatial heterogeneity not only with individual indicators, but through the composite index as well. This type of multiscale study would complement a more in-depth study, such as a country-level assessment. For example, a water security study of the USA could be accompanied by this multiscale water security index. This would allow for the identification of hotspots of insecurity in order to prioritize future studies and or interventions. In addition, a multiscale assessment, as the one conducted herein, can provide a standardized set of indicators that are comparable across scales and allow for the continual monitoring and benchmarking of water security.

Moving forward, this tiered multiscale analysis could be applied to different nested scales such as the river basin and sub-basin scales. It could also be applied to other countries and tailored to desired preferences (e.g. weighting) and objectives (e.g. aggregation). Another direction of future research could be to assess the differences in drivers of insecurity across scales. For example, the administrative scales used in this study could be coupled with socio-economic data in future studies to determine factors associated with high insecurity. Finally, future investigations could include specific area-related concerns such as sea-level rise for coastal areas and salinization of the water supply. Each of these future research directions could be based on the systematic approach laid out within this study.

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