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Vulnerability assessment for loss of access to drinking water due to extreme weather events

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Abstract Climate-related extreme weather events can result in the loss of drinking water access. We assessed the relative vulnerability of 3143 United States (U.S.) counties to loss of drinking water access due to droughts, floods, and cyclones. Five vulnerability assessment models from the literature were compared, each differing in the aggregation method used to combine the three determinants of vulnerability (V) – exposure (E), sensitivity (S), and adaptive capacity (AC). Exposure scores were calculated using historical occurrence data, sensitivity scores were determined from the intrinsic resilience of the drinking water technologies, and adaptive capacity scores were calculated from nine socioeconomic indicators. Our results showed that models $V=E+S+AC$ and $V=E+S–AC$ were the same, as were models $V=E\times S\times AC$ and $V=E\times S\div AC$. Between these two model forms (form 1: $V=E+S+AC$ and $V=E+S–AC$; form 2: $V=E\times S\times AC$ and $V=E\times S\div AC$), scores from one model form could be used to predict scores from the second model form, with R-squared values ranging from 0.61 to 0.82 depending on the extreme weather event type. A fifth model, $V=(E–AC)\times S$ was not found to correlate with any of the other four models. We used $V=E+S+AC$ as our reference model as this resulted in a more uniform distribution of counties in each of the five intervals of vulnerability. Comparing the vulnerability scores identified the counties with greatest vulnerability to losing access to drinking water due to floods, droughts, and cyclones. Our results can

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be used to inform evidence-based decisions such as allocation of resources and implementation of adaptation strategies.

1 Introduction

Loss of access to safe drinking water can occur due to a variety of reasons. Examples of causes of service interruption include planned maintenance, infrastructure failure (e.g., pipe bursts, leaks, or obstructions), and accidental source water contamination (e.g., toxic chemical spills) (San Jose Water Company 2014; Queensland Urban Utilities 2014; The City of Calgary 2014; The New York Times 2014). Operators in charge of water systems should be aware of the possibilities of unplanned infrastructure failures and accidental contamination, and therefore should have maintenance practices, redundancy in processes, and risk management procedures in place to ensure a rapid and appropriate response to these situations (Pollard 2008). Even with these procedures in place, loss of access to drinking water can occur due to extreme weather events such as droughts, floods and cyclones.

Droughts, floods, and cyclones (referred to as hurricanes in the Atlantic and typhoons in the Northwest Pacific) can result in physical damage to drinking water infrastructure and/or contamination and degradation of water quality. Specifically, droughts can cause both a decrease in water supply as well as salinization and increased pollutant concentration due to a reduction in both contaminant mobilization and dilution effect (IPCC 2008); floods and cyclones can cause physical damage to infrastructure from floodwaters and high-velocity winds, respectively, as well as contamination of water supplies from the introduction of debris, silt, pollutants, and sewage (Islam et al. 2007; Kistemann et al. 2002; Mosley et al. 2004). These extreme weather event types are projected to increase in intensity and/or frequency by the Intergovernmental Panel on Climate Change (IPCC) as a result of global climate change (IPCC 2013). Projections for the late (2081–2100) 21st century show a probability of 90–100 % for an increase in frequency, intensity, or amount of heavy precipitation events over most of the mid-latitude land masses and wet tropical regions, a 66–100 % probability for an increase in intensity and/or duration of drought on a regional to global scale, and >50–100 % probability for an increase in intense tropical cyclone activity in the Western North Pacific and North Atlantic (IPCC 2013).

The vulnerability of populations, sectors, or places to climate change and climate variability has been studied using vulnerability assessments as a tool to identify areas that are vulnerable to climate-related effects and events, and to aid in making informed decisions such as the allocation of resources to implement adaptation strategies (Preston et al. 2011). Vulnerability assessment studies have been applied to various fields, including the estimation of coastal area vulnerability to sea-level rise and storm surge flooding (Al-Jeneid et al. 2007; Demirkesen et al. 2008; Kleinosky et al. 2006), and the impact of climate change on renewable groundwater resources and general human welfare (Yusuf and Francisco 2010; Döll 2009). However, vulnerability assessments have not been published in the peer-reviewed literature for the impact of climate related hazards on drinking water access.

The most common method to assess vulnerability is the indicator approach to calculate vulnerability index scores or rankings because of benefits such as (Gbetibouo et al. 2010): 1) scalability – this approach can be applied at the household, county/district, and national level; 2) comparability – calculation of relative vulnerabilities allow for the identification of the most vulnerable systems or places; 3) multi-dimensionality – use of several indicators allows for the multiple dimensions of vulnerability to be captured; and 4) trend analysis – periodic calculation of vulnerability indices can identify trends with time. However, one problem with such indicator-based approaches is the inconsistency in the approach used to aggregate indicators into one composite score. For example, Table 1 lists five different approaches used in the literature to calculate an overall vulnerability index. We could not find any study that provided a justification for selecting one aggregation method over another and only two studies (Cinner et al. 2012; Perch-Nielsen 2010) compared two different aggregation methods and showed that they were highly correlated with each other.

There are therefore two important gaps in the current knowledge that need to be addressed to advance the understanding of vulnerability to loss of access to safe drinking water: 1) vulnerability assessments for the impact of extreme weather events on the loss of drinking water access are not available in the literature; 2) there is no consistent method by which indicators are aggregated in indicator-based approaches. Accordingly, the objectives of this study were to: assess the relative vulnerability of the 3143 United States counties to losing access to drinking water due to floods, droughts, and cyclones; and to compare the vulnerability scores obtained by applying five previously-published vulnerability models that differ in aggregation method. Our results are reported by mapping the vulnerability scores, which allows the counties with the greatest vulnerability to losing access to drinking water to be easily visualized.

2 Methods

2.1 Definition and determinants of vulnerability

Between the IPCC's 4th and 5th Assessment Reports, the definition of vulnerability changed to exclude exposure as a determinant of vulnerability. The IPCC's 4th Assessment Report defines vulnerability as "*the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, the sensitivity and adaptive capacity of that system*" (IPCC 2007). However, in its 5th Assessment Report, vulnerability is re-defined as "*the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts including sensitivity or susceptibility to harm and lack of capacity to cope and adapt*" (IPCC

Table 1 Examples of climate change vulnerability assessment models used in the literature where sub-indices for exposure (E), sensitivity (S), and adaptive capacity (AC) are first calculated prior to combining these sub-indices into an overall vulnerability score

Model #	Equation	References
M1	$V=E+S+AC$	(Borden et al. 2007; Perch-Nielsen 2010; Corobov et al. 2013)
M2	$V=E+S-AC$	(Antwi-Agyei et al. 2012; Cinner et al. 2012; Silva and Lucio 2014)
M3	$V=E\times S\times AC$	(Ferrier and Haque 2003)
M4	$V=E\times S\div AC$	(Cinner et al. 2012; Balica et al. 2009)
M5	$V=(E-AC)\times S$	(Hahn et al. 2009; Shah et al. 2013)

V vulnerability score or ranking, *E* exposure score or ranking, *S* sensitivity score or ranking, *AC* adaptive capacity score or ranking

2014). As the IPCC's new definition of vulnerability was only released in 2013, most studies in the literature calculate vulnerability using the earlier definition and include exposure as a determinant. Accordingly, the vulnerability models used in this study include the exposure term, although we also present in Section 3.4 results of bivariate mapping where exposure is separated from a combined sensitivity and adaptive capacity score.

2.2 Vulnerability assessment models

We considered only models in the literature that first determined sub-indices for exposure (E), sensitivity (S), and adaptive capacity (AC), before combining these sub-indices into an overall vulnerability score. In this way, we ensure that all three determinants are represented in the vulnerability calculation. Table 1 shows the five models that meet these criteria and for which we calculated and compared vulnerability scores and rankings. Additional models in the literature which were not considered either combined all indicators together to determine vulnerability, or only calculated two sub-indices (e.g., E sub-index and a combined S and AC sub-index).

Each of the three determinants – E, S, and AC – were normalized to fall between 0.1 and 1. The minimum value of E, S, and AC was set to 0.1 to avoid final vulnerability scores of 0 for models M3 – M5 (and to avoid division by zero for M4), which would have prevented comparison between counties. The three determinants were weighted equally, as there was no consistent method or justification in the literature for selecting weighting schemes, with some studies using equal weighting (Antwi-Agyei et al. 2012; Ferrier and Haque 2003; Hahn et al. 2009; Shah et al. 2013; Silva and Lucio 2014) and others using unequal weighting (Iglesias et al. 2009; Perch-Nielsen 2010). It has been suggested in several studies (Hahn et al. 2009; Sullivan and Meigh 2005) that expert opinion, participatory consultations, and stakeholder discussion should be used to determine the weighting scheme.

2.3 Indicators of exposure, sensitivity, and adaptive capacity

Table 2 lists the indicators and data sources used to calculate exposure (E), sensitivity (S), and adaptive capacity (AC). An extended version of the Methods including a full description of the steps involved to clean the data and the assumptions made are provided in Online Resource 1.

2.4 Calculation of county exposure (E), sensitivity (S), and adaptive capacity (AC) scores

Historical data on the frequency of droughts, floods, and cyclones from 1950 to 2012 were used as measures of hazard exposure and were obtained from the publically available National Oceanic and Atmospheric Administration (NOAA) Storm Events Database (NOAA 2012). County exposure (E) scores were calculated by normalizing the total number of events in a county during 1950–2012 using the expression

$$County\ \text{exposure}\ (E)\ score\ = a + \frac{(X - X_{\min}) \times (b - a)}{(X_{max} - X_{\min})}, \tag{1}$$

Table 2 List of indicators used to calculate exposure, sensitivity, and adaptive capacity

Vulnerability determinant	Indicator	Data source	Studies supporting use of this indicator
Exposure	Historical data on the frequency of floods, droughts, and cyclones	National Oceanic and Atmospheric Administration (NOAA) Storm Events Database (NOAA 2012)	(Gbetibouo et al. 2010)
Sensitivity	Percent of the population on different drinking water technologies	U.S. Geological Survey's National Water Information System (USGS 2013); U.S. EPA Safe Drinking Water Information System (SDWIS) (USEPA 2012)	N/A
Sensitivity	Intrinsic resilience of each water technology to floods, droughts, and cyclones	(Charles et al. 2010)	(Banerjee 2012)
Adaptive capacity (Financial capital component)	Percent of the population living below the poverty level	American Community Survey, US Census Bureau, 2007–2012 5-year estimates (United States Census Bureau 2014)	(Adger and Vincent 2005; Antwi-Agyei et al. 2012; Borden et al. 2007; Gbetibouo et al. 2010)
Adaptive capacity (Human capital component)	Percent of the population over 25 years old with a high school degree or equivalent	American Community Survey, US Census Bureau, 2007–2012 5-year estimates (United States Census Bureau 2014)	(Borden et al. 2007)
Adaptive capacity (Infrastructure component)	Road density (km per land area)	TIGER/Line® Shapefile and TIGER/Line® Files, US Census Bureau (United States Census Bureau 2013)	(Brooks et al. 2005; Gbetibouo et al. 2010)
Adaptive capacity (Institutional strength component)	Presence of climate change commission and presence of adaptation plan (State level)	(Chou 2012; Levi et al. 2009)	N/A
Adaptive capacity (Technology component)	Research and development expenditure as a percentage of GDP (State level)	National Science Foundation (National Science Foundation 2014)	(Brooks et al. 2005)
Adaptive capacity (Social capital component)	Percent of the population with access to broadband internet (access defined as a download speed of 4 megabits	(Federal Communications Commission 2012)	(Perch-Nielsen 2010)

Table 2 (continued)

Vulnerability determinant	Indicator	Data source	Studies supporting use of this indicator
	per second (Mbps) and upload speed of 1 Mbps)		
Adaptive capacity (Equity component)	GINI coefficient (measure of income inequality, where 0 indicates complete equality and 1 indicates maximum inequality)	American Community Survey, US Census Bureau, 2007–2012 5-year estimates (United States Census Bureau 2014)	(Brooks et al. 2005; Yohe and Tol 2002)
Adaptive capacity (Demographics component)	Life expectancy	American Community Survey, US Census Bureau, 2007–2012 5-year estimates; Institute for Health Metrics and Evaluation (United States Census Bureau 2014; Institute for Health Metrics and Evaluation 2014)	(Brooks et al. 2005; Yohe and Tol 2002)
Adaptive capacity (Risk preparedness component)	Emergency coordination time (State level)	(Centers for Disease Control and Prevention (CDC) 2012)	N/A

where X is the total number of events (i.e., floods or droughts or cyclones) for a specific county, X_{min} is the minimum number of all U.S. counties, X_{max} is the maximum number of all U.S. counties, and a and b define the range within which all E values fall. For floods and droughts, a and b were set to 0.1 and 1, respectively. An exception was made for cyclones, where a and b were set to 0 and 1, respectively. The lower limit, a, was set to 0 for cyclones to reflect the fact that, by definition, inland U.S. counties are not exposed to cyclones. The lower limit, a, was set to 0.1 for floods and droughts because while the historical frequency data may show a count of zero for floods and droughts, all U.S. counties can experience floods and droughts and therefore the lower limit of the range should be a non-zero value.

County sensitivity (S) scores for each hazard were calculated as the population-weighted sum of the intrinsic resilience scores for the different water technology types as given by

$$County\ sensitivity\ (S)\ score\ = \sum_{i=1}^{3} w_i IR_i, \tag{2}$$

where w_i represents the proportion of the county population on each water technology type i, and IR_i represents the intrinsic resilience of water technology type i to the specific hazard. Based on the intrinsic resilience scores defined in Online Resource Table 2, the county sensitivity scores range from 0.1 to 0.7, although the theoretical range would be 0.1 to 1 if a county existed where 100 % of the county population used an unimproved source ($IR_{unimproved}$=1). Results of a sensitivity analysis on the intrinsic resilience scores are also available in Online Resource 5.

County adaptive capacity (AC) scores were calculated by first performing principal component analysis (PCA) using JMP® software on the indicators to obtain synthetic variables (i.e., components) that are independent of one another (description of steps performed and PCA results found in Online Resource 1). To ensure that a high vulnerability score corresponds to greater vulnerability for all five models, the directionality of the indicators was adjusted when needed (see Online Resource 1). Un-normalized AC scores were calculated by weighting each component by the percentage of variance explained. Normalized AC scores were then calculated using equation 1 so that all AC scores were in the range of 0.1–1.0.

3 Results and discussion

3.1 Exposure, sensitivity, and adaptive capacity scores for individual hazards

Exposure, sensitivity, and adaptive capacity scores were calculated for the 3143 counties of the United States for floods, droughts, and cyclones separately. Figure 1 shows the results for floods, with corresponding figures for droughts and cyclones presented in Figures A1 and A2 of Online Resource 2. The maps are displayed in five intervals classified using the Jenks natural breaks classification method in ArcGIS 10.1, where red and dark green correspond to counties with the interval of highest and lowest exposure, respectively. Natural breaks was selected as the display method instead of the quantile method because the quantile method can lead to two counties with similar scores being placed in two different intervals due to the requirement of equal number of counties per interval (e.g., natural breaks method may classify 10, 30, 20, 5, and 35 counties into five intervals, while the quantile method would classify 20 counties into each of the five intervals). For example, Fig. 1a and d illustrate the differences in flood exposure in the U.S. by the natural breaks and quantile methods, respectively.

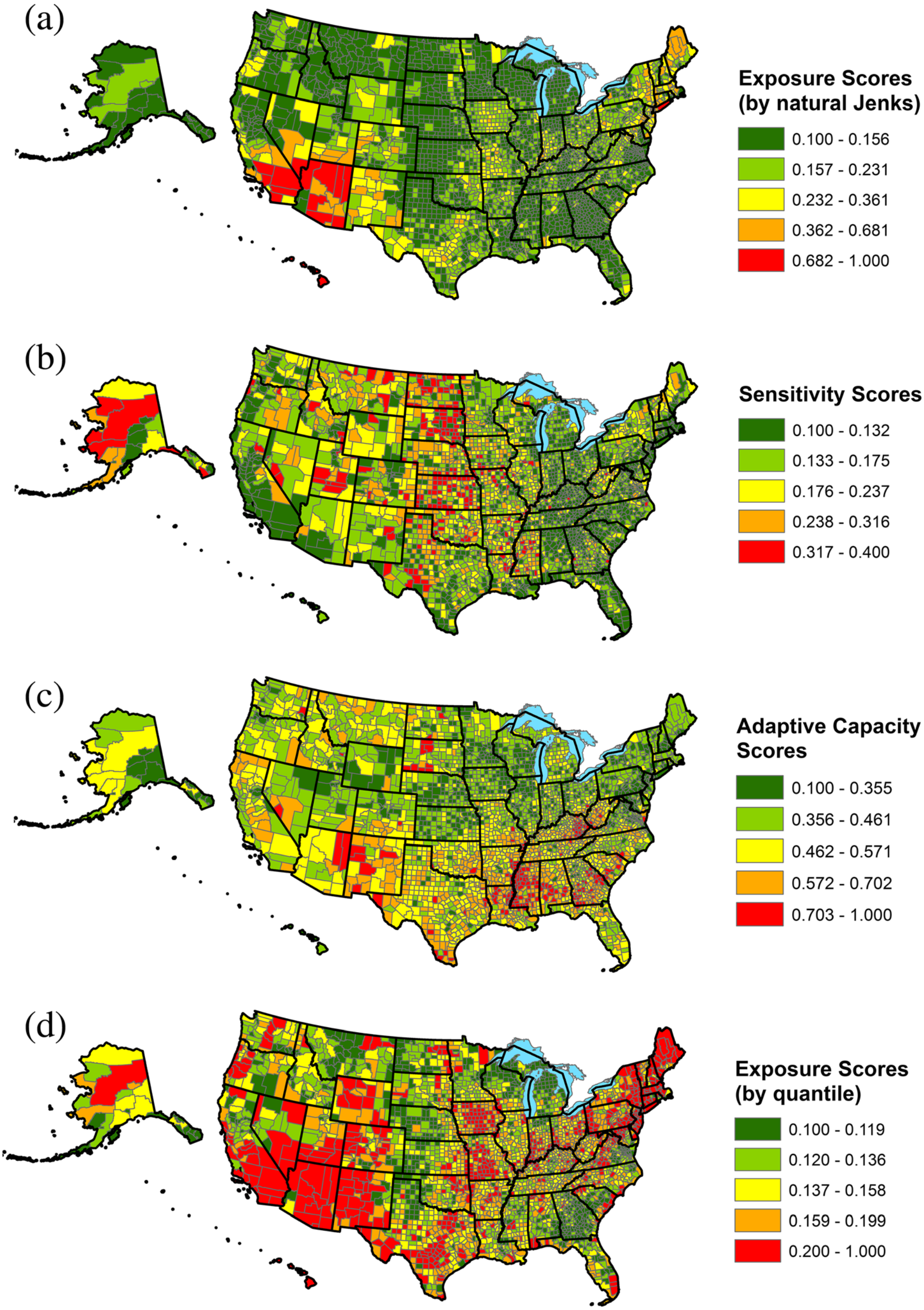

Fig. 1 Scores for **a** exposure displayed by the natural Jenks method, **b** sensitivity, **c** adaptive capacity, and **d** exposure displayed by the quantile method for floods

Flood exposure (Fig. 1a) was highest in the northeast (particularly in Maine) and southwest (southern California, Arizona) of the U.S., with counties in central and northern U.S. typically in the lowest interval of exposure. Drought exposure (Figure A1a in Online Resource 2) was higher in the southern U.S. with patches of drought also occurring in some of the counties in the eastern U.S. states (Delaware, New Jersey, Connecticut, North and South Carolina). Cyclone exposure (Figure A2a in Online Resource 2) was geographically limited to the southeast coastline of the U.S. from North Carolina to Louisiana. Flood, drought, and cyclone sensitivity maps (Fig. 1b and Figures A1b and A2b in Online Resource 2) show that for all three, while sensitivity is widely distributed geographically, counties belonging to the two highest intervals of sensitivity, as given by the red and orange colours, are typically in the central U.S. Adaptive capacity, which reflects the county's ability to cope with extreme weather events is presented in Fig. 1c and shows that counties with increased adaptive capacity (dark green) are located in the northern part of the U.S., while New Mexico, Louisiana, Mississippi, and Alabama primarily show counties in the lowest or second lowest interval of adaptive capacity.

3.2 Comparison of vulnerability scores calculated using five aggregation methods

Vulnerability scores were calculated by aggregating the exposure, sensitivity, and adaptive capacity scores according to the five models, M1-M5, listed in Table 1. In the case of cyclones, when the exposure score was 0, the corresponding vulnerability scores for models M1, M2, and M5 were set to the lowest possible vulnerability value (from counties with non-zero exposure scores) to ensure that they were classified into the interval of lowest vulnerability. Comparison between models was performed by plotting the vulnerability scores from one model against scores from a second model for all possible model pairings (i.e., M1 vs M2, M1 vs M3, etc.). The data points were then fit to a linear or polynomial expression to determine whether a relationship existed between the vulnerability scores calculated from the two models. Online Resource Table 5 presents the model pairings, type of fitted regression equation used, and corresponding R-squared values, for all possible combinations.

From the R-squared values, we see that models M1 ($V=E+S+AC$) and M2 ($V=E+S-AC$) are highly correlated (i.e., knowing the M1 scores allows M2 scores to be calculated), as are models M3 ($V=E\times S\times AC$) and M4 ($V=E\times S\div AC$). This reduces the number of different aggregation model types to three: M1, M3, and M5 – for simplicity, we chose M1 and M3 to represent the M1/M2 and M3/M4 pairings. Of the remaining three models, R-squared values obtained from fitting an equation between vulnerability scores of M1 and M3 ranged from 0.61 to 0.82 depending on the extreme weather event type. These results are similar to the findings of Cinner et al. (2012) who reported $R=0.9$ for models M2 and M4 in the vulnerability of coral reefs to climate change induced stresses and the findings of Perch-Nielsen (2010) who found a high correlation (97-99 % depending on the weighting scheme used) between the arithmetic mean (similar to model M1) and geometric mean (similar to model M3) for the vulnerability of beach tourism to climate change. Model M5, $V=(E–AC)\times S$, was not correlated to any other model.

Between models M1 and M3, there is no justification for choosing one model over the other. We found that the distribution of counties into the five intervals of vulnerability was more uneven (percentage of counties per interval) using model M3. For example, while the distribution of counties per interval from lowest to highest vulnerability for floods using model M1 was 19, 31, 28, 18, and 4 %, the corresponding distribution using model M3 was 46, 34, 16, 4, and 1 % from M3. Similar results were obtained for droughts and cyclones. As model M1 represents four out of the five models, we present and discuss the results for M1 in the remainder of the main text, with results for M2-M5 available in Online Resource 4.

3.3 Vulnerability calculated from model M1: V=E+S+AC

Figure 2a–c shows the vulnerability maps for floods, droughts, and cyclones calculated using model M1. Flood vulnerability was highest for parts of California, Nevada, and New Mexico, and for almost all counties in Arizona. Counties next to the Great Lakes (corresponding to

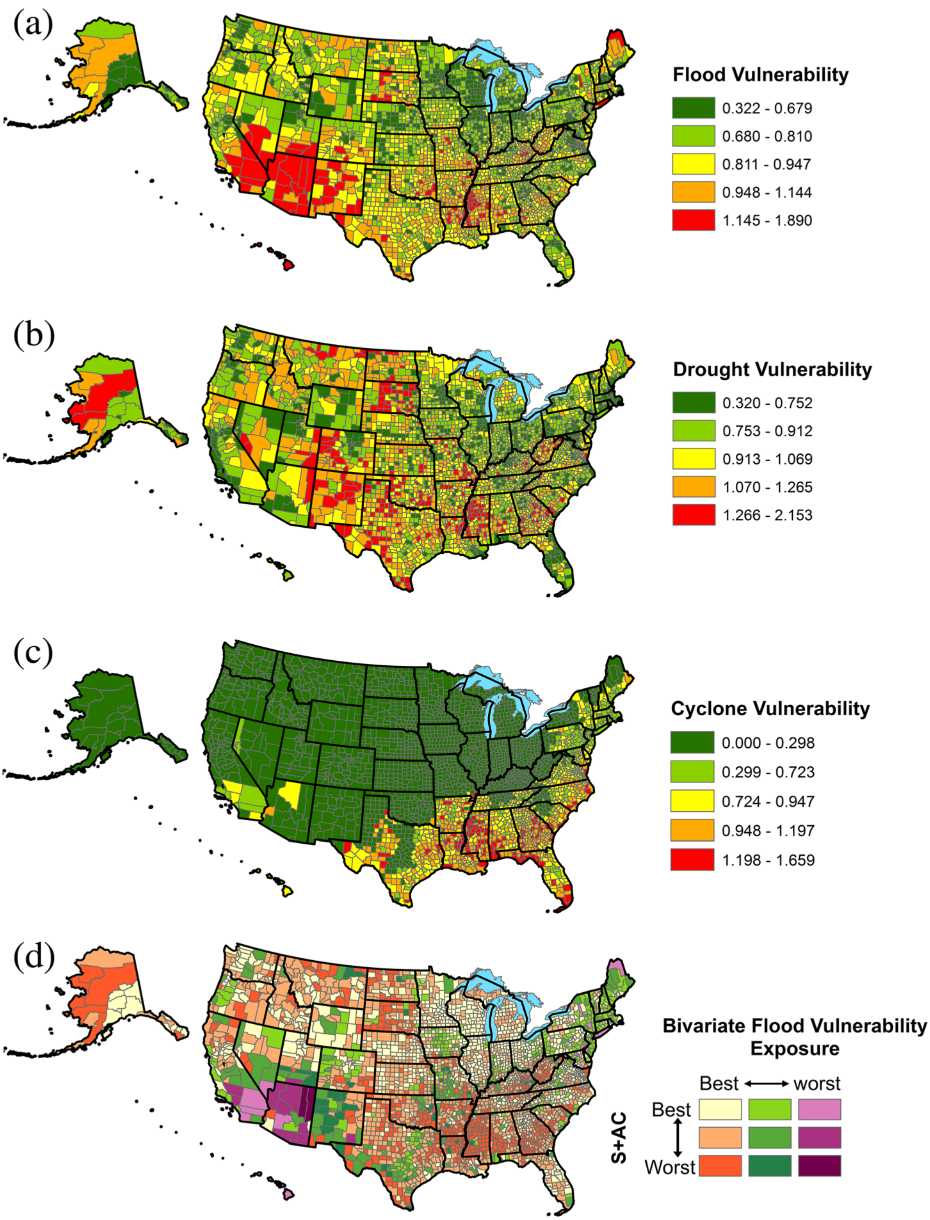

Fig. 2 Vulnerability to **a** floods, **b** droughts, and **c** cyclones calculated using model M1: $V=E+S+AC$; **d** bivariate mapping flood vulnerability shown as a function of exposure and a combined sensitivity and adaptive capacity score

counties in the states of Wisconsin, Illinois, Indiana) were generally in the lowest or second-lowest interval of vulnerability. For droughts, vulnerability was more uniformly distributed across states; however, counties in Indiana, Ohio, and Pennsylvania were generally in the lowest or second-lowest interval of vulnerability, while most states in central U.S. had several counties in the highest or second highest interval. Cyclone vulnerability was dictated by its exposure pattern and generally restricted to the east coast, with almost all counties in Mississippi placing in the highest or second highest interval of vulnerability. No one component (E, S, AC) of vulnerability was found to always have a greater impact on vulnerability than the other components. Comparison of flood vulnerability in Fig. 2a with the E, S, and AC components of flood from Fig. 1 shows that all components can have a dominant effect on whether a county falls into the lowest or highest interval of vulnerability.

The vulnerability maps shown in Fig. 2a–c represent county-level vulnerability. Two additional vulnerability metrics that consider county population and county land area can also be calculated. Population-weighted vulnerability, which takes into account county population, can be calculated by multiplying the county vulnerability score by the fraction of the U.S. population living in that county. For example, results for population-weighted flood vulnerability show that counties in the interval of highest vulnerability generally coincide with counties where large populations reside (see Online Resource 6). An areal county vulnerability, where the normalized exposure scores are calculated using total number of events divided by county land area, can also be calculated (see Online Resource 7). Areal county vulnerability takes into account the fact that the exposure scores are likely to be influenced by the land area of the county, where larger counties would be expected to experience more event counts than smaller counties. For example, results for flood vulnerability show that large counties in California and Arizona which are in the highest interval of vulnerability when county land area is not taken into account (Fig. 2a) move into intermediate intervals of vulnerability when areal county vulnerability is estimated. However, in this study, (non-areal) county-level vulnerability was chosen as the unit of interest because decisions regarding the types and amount of investment are made at the county administrative level and therefore total event counts and not counts per unit area are the metric of interest.

3.4 Separation of exposure from sensitivity and adaptive capacity

To address the IPCC's revised definition of vulnerability, which in contrast to previous definitions excludes exposure and focuses only on sensitivity and adaptive capacity, we use bivariate mapping to visualize our results. Figure 2d presents the bivariate map for floods, where we used a combined sensitivity and adaptive capacity index to represent the new vulnerability definition and we used the form $S+AC$, which is analogous to model M1. Since bivariate mapping requires $n \times n$ number of colours, where n is the number of intervals for each variable, we re-classified by natural breaks the exposure and $S+AC$ index into three intervals each (best, medium, and worst), giving nine different colours. As seen in Fig. 2d, the bivariate scheme identifies southern California and Arizona to have both the worst exposure and the worst combined sensitivity and adaptive capacity for floods. Approximately half the counties were found to be in the lowest interval of exposure but to have medium or worst combined sensitivity and adaptive capacity. The advantages of bivariate mapping is that it allows exposure to be separated from sensitivity and adaptive capacity and thus counties with a high E and low $S+AC$ can be differentiated from counties with a high E and high $S+AC$. However, the division of E and $S+AC$ into only three classes each – in order to minimize confusion from a 5×5 colour scheme – leads to loss of the details provided by Figs. 1 and 2a–c.

In addition to separating out exposure from sensitivity and adaptive capacity, bivariate mapping can also be used to visualize the vulnerability of a county in comparison to county population. An example using floods is presented in Online Resource 8 and identifies counties that are highly populated with low vulnerability and counties with low population and high vulnerability. These results can be used by policy makers when making decisions on where to focus climate change adaptation efforts.

3.5 Study limitations

We used the NOAA Storm Events Database to obtain historical frequency of floods, droughts, and cyclones; however, the storm data disclaimer states that information from some of the sources may be unverified by the National Weather Service (NOAA 2013). As such, it is possible that inaccurate reporting, under-reporting, or over-reporting of events may occur. Reporting may also be influenced by geographic location, as seen, for example, by the distinct geographic discontinuities across the state border for drought between northern Oklahoma and southern Kansas (see Online Resource 2). On the other hand, no discontinuity across the state border was observed for drought in eastern Utah and western Colorado. Within each of the three hazards, no differentiation was made between event types nor event severity. For example, flood event types of flash floods and snowmelt flooding may differ in origin – the former may be due to heavy precipitation while the latter due to unseasonal snow melt – and are not reflected in the exposure scores. While the inclusion of severity or intensity of an event would have been ideal, this data was not available for the events reported by the NOAA Storm Events Database. For example, events that were classified as droughts had a D2 or higher classification based on the U.S. Drought Monitor; however, it was not possible to distinguish if a drought was a D2 or D3 event. A county that experienced a single exceptional (D4) drought would therefore have a lower level of exposure than a county that experienced multiple severe (D2) droughts.

Sensitivity scores were calculated based on the qualitative assessment of the intrinsic resilience of drinking water systems to the three extreme weather event types and required several assumptions: (i) we used a size cut-off for piped drinking water systems in order to classify these systems as utility-managed or community-managed systems; (ii) it was assumed that the difference in resilience between low and medium resilience was the same as that between medium and high resilience; and therefore the numerical values assigned to low, medium, and high resiliency were equally spaced. Changes to the size cut-off used or the values assigned to intrinsic resilience, particularly for high resilience, would alter the sensitivity scores. Adaptive capacity scores were calculated using indicators for determinants of adaptive capacity and were limited by the data that was available. Use of several indicators per determinant and validation of the selection of these indicators would be desirable. Finally, neither the resilience scores nor the indicators for adaptive capacity account for loss of access to drinking water due to damage to energy infrastructure, which affects systems operations.

4 Conclusions

In this study, we assessed the relative vulnerability of all U.S. counties to losing access to drinking water due to floods, droughts, and cyclones. We calculated and compared vulnerability scores using five models from the literature and found that four of the models were correlated with each other, with R-squared values ranging from 0.61 – 1.0 depending on the extreme weather event type. A fifth model, $V=(E–AC)\times S$, did not correlate to any of the other four models. This suggests that the aggregation method is important in determining relative vulnerability and different models should be compared.

Comparison of a county's relative exposure, sensitivity, adaptive capacity, and vulnerability in Figs. 1 and 2 demonstrates that no one component is responsible for the final vulnerability score in all counties, but rather any one component may dominate in some counties while a different component dominates in other counties. The geographic distribution of vulnerability differed depending on the extreme weather event type considered. Thus, while national climate change adaptation policies may be proposed, region-specific and locally adapted policies are also needed to address the differences in vulnerability.

The results describe the relative vulnerability of U.S. counties to loss of drinking water access and allows for comparisons between counties, which can be used to inform decision makers on allocation of resources and areas in which to focus efforts (e.g., increasing adaptive capacity). Using the indicator approach to construct the vulnerability scores allows for updates to indicators and the potential for future incorporation of additional indicators that measure utility level adaptation, thus allowing individual utilities to calculate their vulnerability and reflect on different adaptation options. The current relative vulnerability scores also can be used as a reference baseline for: (1) comparison to future vulnerability, which would be calculated using future projections for hazard exposure; and (2) evaluation of how specific adaptation measures implemented by a county would affect its vulnerability.

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References

Adger WN, Vincent K (2005) Uncertainty in adaptive capacity. Compt Rendus Geosci 337:399–410

Al-Jeneid S, Bahnassy M, Nasr S et al (2007) Vulnerability assessment and adaptation to the impacts of sea level rise on the Kingdom of Bahrain. Mitig Adapt Strateg Glob Chang 13:87–104

Antwi-Agyei P, Fraser EDG, Dougill AJ et al (2012) Mapping the vulnerability of crop production to drought in Ghana using rainfall, yield and socioeconomic data. Appl Geogr 32:324–334

Balica SF, Douben N, Wright NG (2009) Flood vulnerability indices at varying spatial scales. Water Sci Technol J Int Assoc Water Pollut Res 60:2571–2580

Banerjee, O. (2012). Evaluating country-level population vulnerabilities to water access due to climate related hazards using high spatial resolution methods. BS Thesis, University of North Carolina at Chapel Hill, Chapel Hill, NC.

Borden KA, Schmidtlein MC, Emrich CT et al (2007) Vulnerability of U.S. cities to environmental hazards. J Homeland Secur Emerg Manag 4(2), article 5

Brooks N, Adger WN, Kelly PM (2005) The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. Glob Environ Chang 15:151–163

Centers for Disease Control and Prevention (CDC) (2012). Public Health Preparedness: 2012 State-By-State Report on Laboratory, Emergency Operations Coordination, and Emergency Public Information and Warning Capabilities. Available at: http://www.cdc.gov/phpr/pubs-links/2012/documents/2012State-By-State_Preparedness_Report.pdf. Accessed 21 Feb 2013

Charles, K., Pond, K., Pedley, S. et al. (2010). Vision 2030 The resilience of water supply and sanitation in the face of climate change: Technology projection study. Available at: http://www.who.int/water_sanitation_health/publications/vision_2030_technology_projection_report.pdf. Accessed 04 Jan 2014

Chou, B. (2012). Ready or not: An evaluation of state climate and water preparedness planning, natural resources defense council document. Available at: http://www.nrdc.org/water/readiness/files/Water-Readiness-full-report.pdf. Accessed 07 Feb 2014

Cinner JE, McClanahan TR, Graham NAJ et al (2012) Vulnerability of coastal communities to key impacts of climate change on coral reef fisheries. Glob Environ Chang 22:12–20

Corobov, R., Sirodoev, I., Koeppel, S. et al. (2013). Assessment of climate change vulnerability at the local level: a case study on the Dniester River Basin (Moldova). *The Scientific World Journal* : article ID 173794.

Demirkesen AC, Evrendilek F, Berberoglu S (2008) Quantifying coastal inundation vulnerability of Turkey to sea-level rise. Environ Monit Assess 138:101–106

Döll P (2009) Vulnerability to the impact of climate change on renewable groundwater resources: a global-scale assessment. Environ Res Lett 4:035006

Federal Communications Commission (2012). Eighth Broadband Progress Report. Available at: http://www.fcc.gov/document/progress-made-broadband-deployment-availability-gaps-remain. Accessed 4 Feb 2013

Ferrier N, Haque CE (2003) Hazards risk assessment methodology for emergency managers: a standardized framework for application. Nat Hazards 28:271–290

Gbetibouo GA, Ringler C, Hassan R (2010) Vulnerability of the South African farming sector to climate change and variability: an indicator approach. Nat Res Forum 34:175–187

Hahn MB, Riederer AM, Foster SO (2009) The Livelihood Vulnerability Index: a pragmatic approach to assessing risks from climate variability and change—a case study in Mozambique. Glob Environ Chang 19:74–88

Iglesias A, Garrote L, Cancelliere A et al (eds) (2009) Coping with drought risk in agriculture and water supply systems. Spring Science+Business Media B.V, The Netherlands

Institute for Health Metrics and Evaluation (2014). Left behind: Widening disparities for males and females in US county life expectancy, 1985–2010. Available at: http://www.healthdata.org/research-article/left-behind-widening-disparities-males-and-females-us-county-life-expectancy-1985. Accessed 15 Jul 2014

Intergovernmental Panel on Climate Change (IPCC) (2007). Climate Change 2007: Impacts, Adaptation and Vulnerability. Group II Contribution to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Available at: http://www.ipcc.ch/publications_and_data/ar4/wg2/en/contents.html

Intergovernmental Panel on Climate Change (IPCC) (2008). Climate change and water: IPCC Technical Paper VI. Available at: https://www.ipcc.ch/publications_and_data/publications_and_data_technical_papers.shtml

Intergovernmental Panel on Climate Change (IPCC) (2013). Climate Change 2013: The Physical Science Basis. Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Available at: http://www.ipcc.ch/report/ar5/wg1/

Intergovernmental Panel on Climate Change (IPCC) (2014). Climate Change 2014: Impacts, Adaptation, and Vulnerability. Summary for Policymakers. Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Available at: http://www.ipcc.ch/report/ar5/wg2/

Islam MS, Brooks A, Kabir MS et al (2007) Faecal contamination of drinking water sources of Dhaka city during the 2004 flood in Bangladesh and use of disinfectants for water treatment. J Appl Microbiol 103:80–87

Kistemann T, Claben T, Koch C et al (2002) Microbial load of drinking water reservoir tributaries during extreme rainfall and runoff. Appl Environ Microbiol 68:2188–2197

Kleinosky LR, Yarnal B, Fisher A (2006) Vulnerability of Hampton Roads, Virginia to storm-surge flooding and sea-level rise. Nat Hazards 40:43–70

Levi, J., Vinter, S., Gratale, D., et al. (2009). Health Problems Heat Up: Climate Change and The Public's Health. Available at: http://healthyamericans.org/reports/environment/TFAHClimateChangeWeb.pdf. Accessed 20 Jan 2013

Mosley LM, Sharp DS, Singh S (2004) Effects of a tropical cyclone on the drinking-water quality of a remote Pacific island. Disasters 28:405–417

National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center (2012). Storm Events Database. Available at: http://www.ncdc.noaa.gov/stormevents/ftp.jsp. Accessed 29 Jan 2013

National Oceanic and Atmospheric Administration (NOAA). National Climatic Data Center (2013) Storm Data FAQ Page. Available at: http://www.ncdc.noaa.gov/stormevents/faq.jsp. Accessed 8 Oct 2013

National Science Foundation (2014). Science and Engineering Indicators 2014: Financial Research and Development Outputs R&D as a Percentage of Gross Domestic Product. Available at: http://www.nsf.gov/statistics/seind14/index.cfm/chapter-8/c8s4o40.htm. Accessed 15 Jul 2014

Perch-Nielsen SL (2010) The vulnerability of beach tourism to climate change—an index approach. Clim Chang 100:579–606

Pollard SJT (2008) Risk management for water and wastewater utilities. IWA Publishing, London

Preston BL, Yuen EJ, Westaway RM (2011) Putting vulnerability to climate change on the map: a review of approaches, benefits, and risks. Sustain Sci 6:177–202

Queensland Urban Utilities (2014). Water service interruptions. Available at: http://www.urbanutilities.com.au/faults-and-interruptions/water-service-interruptions. Accessed 24 Nov 2014

San Jose Water Company (2014). Service Interruptions. Available at: http://www.sjwater.com/for_your_home/home_customer_care/service_interruptions/. Accessed 24 Nov 2014

Shah KU, Dulal HB, Johnson C et al (2013) Understanding livelihood vulnerability to climate change: applying the livelihood vulnerability index in Trinidad and Tobago. Geoforum 47:125–137

Silva BKN, Lucio PS (2014) Indicator of agriculture vulnerability to climatic extremes. A conceptual model with case study for the northeast Brazil. Atmos Clim Sci 2:334–345

Sullivan C, Meigh J (2005) Targeting attention on local vulnerabilities using an integrated index approach: the example of the climate vulnerability index. Water Sci Technol J Int Assoc Water Pollut Res 51:69–78

The City of Calgary (2014). Water main and water pipe breaks. Available at: http://www.calgary.ca/UEP/Water/Pages/construction-projects/Water-main-repairs-and-maintenance/Water-Main-Breaks-FAQ.aspx. Accessed 24 Nov 2014

The New York Times (2014). Thousands without water after spill in West Virginia. Available at: http://www.nytimes.com/2014/01/11/us/west-virginia-chemical-spill.html?_r=0. Accessed 26 Nov 2014

U.S. Geological Survey (USGS) (2013). Estimated use of water in the United States county-level data for 2005. Available at: http://water.usgs.gov/watuse/data/2005/. Accessed 23 Mar 2013

United States Census Bureau (2013). TIGER/Line Shapefiles and TIGER/Line Files. Available at: https://www.census.gov/geo/maps-data/data/tiger-line.html. Accessed 20 Mar 2013

United States Census Bureau (2014). American Community Survey. Available at: http://factfinder2.census.gov. Accessed 30 Oct 2014

United States Environmental Protection Agency (USEPA) (2012). SDWISFED Drinking Water Data. Available at: http://water.epa.gov/scitech/datait/databases/drink/sdwisfed/pivottables.cfm#summary. Accessed 20 Mar 2013

Yohe G, Tol RSJ (2002) Indicators for social and economic coping capacity—moving toward a working definition of adaptive capacity. Glob Environ Chang 12:25–40

Yusuf, A. A., Francisco, H. (2010). Hotspots! Mapping climate change vulnerability in Southeast Asia. Available at: http://www.eepsea.org/o-k2/view-item/id-432/Itemid-389/