Revising NCEI's Climate Extremes Index and the CDC's Social Vulnerability Index to Analyze Climate Extremes Vulnerability across the United States

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ABSTRACT: The occurrence of extreme weather and climate events has increased in recent decades. This increasing frequency has adversely impacted economic and health outcomes, leading to an increasingly urgent need to study climate extremes. The National Centers for Environmental Information (NCEI) created the Climate Extremes Index (CEI) in 1996 to quantify climate extremes. In this article, we explore the potential for enhancing the CEI via the use of the Z-score statistic to calculate the CEI on a numerical scale, to increase usability at smaller spatial scales, and to allow the creation of a new climate Extremes Vulnerability Index (EVI). The EVI combines the results from the revised CEI with values from the Social Vulnerability Index from the Centers for Disease Control and Prevention (CDC). The EVI can be used by policy-makers, planners, and the public to understand a subregion's vulnerability to climate extremes. This information from the EVI could then be used to implement policies and changes in infrastructure that mitigate risk in vulnerable climate divisions. In a trial application, it is found that the southeastern and portions of the central United States had the highest levels of vulnerability for the abnormal month of December 2015.

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Since the Industrial Revolution of the nineteenth century, anthropogenic climate change has manifested itself in the increased frequency of temperatures and precipitation that are significantly different from normal values, known as climate extremes (IPCC 2014; Reidmiller et al. 2018). Studying climate extremes is increasingly urgent because the rising number of extreme events has adversely impacted economic and health outcomes. For example, a multiday heatwave throughout much of the eastern United States in July 2019 presented an increased risk of heat stroke to many residents unaccustomed to temperatures above 32.2°C (90°F) (Peltz 2019). There is also now an increased risk of economic disruption as millions of Americans living in coastal areas continue to sell their homes and move to avoid rising sea levels (Gopal 2019). The impact of climate extremes also extends to the insurance industry. Increasing climate variability and occurrence of extremes can cause deviations from the estimation of future health insurance costs, and this will have “considerable financial consequences” (Owen 2019).

To educate the public and policy-makers about climate extremes, several indices measuring them have been created. One of the first, the Climate Extremes Index (CEI) from the National Centers for Environmental Information (NCEI), formerly the National Climatic Data Center (NCDC), was created in the 1990s to quantify the extremes that the country as a whole was experiencing (Karl et al. 1996). However, the CEI has remained complex enough that it is very difficult for the public to interpret, and it has only been minimally updated since its inception (Gleason et al. 2008). In this paper, the CEI is recalculated using the Z-score statistic (Larson and Farber 2006) to calculate the CEI on a numerical scale and increase usability at smaller spatial scales. After recalculating the CEI, we combine it with values from the Centers for Disease Control and Prevention’s (CDC) Social Vulnerability Index (SVI; Flanagan et al. 2011) to create a climate Extremes Vulnerability Index (EVI) that can be used by policy-makers, planners, and the public to identify areas of the United States that may be more at risk of experiencing climate extremes.

Climate vulnerability and a framework for analysis

An important, and emerging, application of climate extremes data is to human health and vulnerability (Bell 2018; Crimmins et al. 2016; Portier et al. 2010). Climate vulnerability is defined by the Intergovernmental Panel on Climate Change (IPCC) as the degree to which a system is exposed to, and unable to cope with, adverse climate conditions (IPCC 2007). This means that for the assessment of climate vulnerability to be accurate, it should be based not only on how often certain climate conditions occur, but also on social factors. Therefore, a more comprehensive way to characterize climate vulnerability is to represent it as a function of exposure, sensitivity, and adaptive capacity (KC et al. 2015), as in the equation below:

$$\text{Vulnerability} = f(\text{Exposure, Sensitivity, and Adaptive Capacity}). \quad (1)$$

Exposure to climate variables (temperature, precipitation, and extreme events such as hurricanes) forms the basis for exposure. Sensitivity is a measure of the social and demographic makeup of a system, and adaptive capacity is the measure of a system’s ability to adjust to climate related factors (KC et al. 2015, taken from IPCC 2007).

KC et al. (2015) used this framework to form the basis of a vulnerability index, which calculates climate change vulnerability based on climate exposure as well as social vulnerability (sensitivity and adaptive capacity combined):

$$\text{Climate Change Vulnerability} = \text{exposure} + \text{social vulnerability}. \quad (2)$$

Both factors had equal weighting in the computation of this index, corresponding to the additive model of calculating indices. Using additive models means that the final vulnerability value

calculated will be equally dependent on all components, as opposed to being more dependent on or weighted toward one or two elements (Allison et al. 2009; Cutter et al. 2003; Reid et al. 2009).

While calculating a vulnerability index is an important step toward communicating potential risks to the public, the more important step is representing the results in a way that is easy for any user to understand. A study conducted by Oxfam sought to produce maps that illustrated vulnerable communities by using a similar framework to that of KC et al. (2015). The results are depicted in the form of bivariate analysis maps that visualize the convergence of climate hazards and social hazards (Oxfam America 2018). From the scale on these images, it is easy to identify the regions of strongest convergence of climate and social factors.

These two methods of KC et al. (2015) and Oxfam can be combined to determine and visualize vulnerability to climate extremes to help communities take preventative action to minimize the risk to their health and well-being. To use this framework to calculate an Extremes Vulnerability Index, we made use of two indices: the Climate Extremes Index from the NCEI (serving as the exposure component) and the Social Vulnerability Index from the CDC (serving as the social vulnerability component).

Physical exposure: The Climate Extremes Index (CEI)

The CEI and its strengths and weaknesses. The original CEI is defined in Karl et al. (1996) as being the arithmetic average of five indicators of the percentage of the contiguous United States experiencing extremes of each indicator. NCEI uses the term “step” to refer to each indicator in the CEI. The term “component” is used here. The five components selected were

- 1) maximum temperatures much below normal and maximum temperatures much above normal ($T_{\max}$ %);
- 2) minimum temperatures much below normal and minimum temperatures much above normal ($T_{\min}$ %);
- 3) severe drought (representing a severe lack of moisture) and severe moisture surplus (Moisture%);
- 4) greater-than-normal amounts of extreme 1-day precipitation totals, measured by comparing the proportion of daily rainfall to analysis period total across all grid points (1-day%);
- 5) greater-than-normal number of days with precipitation and greater-than-normal number of days without precipitation, used as a way to gauge total number of days with rainfall per analysis period (Precip_days%).

The first step in calculating the CEI was determining the threshold for “extreme” values within each component. Karl et al. (1996) defined the extreme portion of each dataset as the portion falling in the highest 10% of the dataset (high extremes), or the lowest 10% of the dataset (low extremes). To calculate the final product, the percentage of the country that was experiencing extremes in each of the five components was first determined. The final index value was calculated by averaging all percentages together to come up with a total percentage of the United States experiencing extreme conditions:

$$\text{CEI} = [(T_{\max} \%) + (T_{\min} \%) + (\text{Moisture}\%) + 2 \times (1\text{-day}\%) + (\text{Precip_days}\%)] / 5. \quad (3)$$

Since the calculation is based on the highest and lowest 10% of each indicator, the expectation is that about 20% of the country on average should be experiencing extreme conditions. Values not equal to this amount indicate a change in the expected area of the United States experiencing extreme weather patterns (Karl et al. 1996; Gleason et al. 2008).

Although this index serves as a good first step to quantifying climate extremes, using the operational CEI to calculate a vulnerability index is challenging due to several limitations:

- The assumption that 20% of the United States is experiencing extremes in climate is unrealistic when there are five different indicators included in this index. Analysis of the top and bottom tails of a distribution is not a very robust technique, as demonstrated in Fig. 1. When using percentiles to define extreme values, the same number of data points will be considered to be extreme, regardless of distance from the mean. Because raw values are not being compared to a value like a mean value, there can be situations in which a value that falls in the highest or lowest 10th percentile of a data distribution is not actually extreme.
- The overall index merely indicates that extreme conditions are occurring, not where extremes are occurring or how extreme those values are.
- The original CEI produces a value for the entire country, and a recent update (Gleason et al. 2008) produces a CEI value for nine regions within the United States. However, the CEI would greatly benefit from a climate-division-level analysis because it would allow citizens to see what the trend is for climate extremes in their area and how they could be impacted in the future.

Other climate extremes indices. Since the inception of the CEI, several other indices with the goal of calculating and communicating climate extremes have been developed, and there are many concepts that could be taken from these indices and implemented in the calculation of a revised CEI. The Actuaries Climate Index (ACI) is an index that is expressed as a numerical index of standard deviations from the mean of the reference period of 1961–90 that places a high priority on interpretability by nonscientists (AAA et al. 2016). A similar index, the Australian Actuaries Climate Index (AACI), expresses index values as a numerical scale as well, but this index uses 1981–2010 values as the reference period. Since this period is the most current and complete 30-yr period available, it is a reliable period to use as a baseline for comparisons, even though the conditions during this period are not necessarily typical because it contains the climate change signal (Actuaries Institute 2018). Modifications of the CEI, the Australian modified CEI (mCEI) and daily modified CEI (dmCEI), address two limitations of the original CEI: the lack of a description of the trend of extremes (toward the upper or lower end of a distribution), and the lack of a regional breakdown of the CEI (Gallant and Karoly 2010).

Fig. 1. Ten temperature simulations, with 100 temperature values per simulation. For each simulation, the mean is 75 and the standard deviation is 5. Values in black are those that are less than the 90th percentile and greater than the 10th percentile. Values in red and blue respectively represent values exceeding the 90th percentile and values less than the 10th percentile. The pink and light blue lines are drawn at +2 and –2 standard deviations from the mean, respectively, and the red and dark blue lines are drawn at +3 and –3 standard deviations, respectively.

The Z-score statistic. The temperature and precipitation datasets used in the calculation of the CEI have two different distributions, as precipitation is never normally distributed (Wilks 1989). To recalculate the CEI to quantify the extremity of values, different statistical techniques should be applied to the datasets that derive the components of the CEI to account for the irregularities that may be within each dataset. To maintain a similar format when calculating the final index, a statistic is needed that can be used to identify extremes in non-normal data distributions. The Z score is one such statistic (Larson and Farber 2006). A Z score is mathematically defined as

$$z = \frac{\text{Value} - \text{Mean}}{\text{Standard Deviation}} = \frac{x - \mu}{\sigma}. \quad (4)$$

In this equation, x represents the data value, μ represents the mean of the dataset, and σ represents the standard deviation of the dataset. Thus, the Z score is the number of standard deviations a data value lies from the mean in the dataset it comes from (Larson and Farber 2006). The Z score is rigorously quantified by Chebyshev's Rule (Shafer and Zhang 2017), which applies to any probability distribution with a finite mean and finite variance, normal or otherwise, including all weather and climate datasets.

Chebyshev's Rule mathematically describes how all data points must behave with respect to their own mean and standard deviation. More precisely, Chebyshev's Theorem states that the proportion of any dataset lying within k standard deviations of the mean is at least

$$\left(1 - \frac{1}{k^2}\right) \times 100\%. \quad (5)$$

This statement gives a description of the number of data observations that are expected to lie within a certain number of standard deviations of the mean of a dataset. When $k = 3$, or three standard deviations, this statement equals 88.9%. This means that at least 88.9% of the data must lie within three standard deviations of the mean (Larson and Farber 2006). Since this metric also uses units of standard deviation, Z scores are actual values of k . Applying this math to the Z scores of any dataset means that at least 89% of the data will have a Z score within ± 3 . This also serves as a statement about data falling outside of this interval. In the context of this work, any data point with a Z score of absolute value larger than 3 is considered to be extreme.

Revising the CEI: Data sources. For our revised CEI, data for each component came from NCEI datasets. Data for the calculation of Components 1 (maximum temperature) and 2 (minimum temperature) in both the operational and revised CEI come from the nClimGrid dataset, which contains temperature data at a 5-km resolution (NCEI 2018, unpublished data; NCEI 2020; Vose et al. 2014a). For drought and moisture surplus (Component 3), Palmer Drought Severity Index (PDSI) values are used (Palmer 1965; NCEI 2018, unpublished data). Regional PDSI values are used to calculate the original CEI; climate division level values are used in this project to calculate the revised CEI. The data used to calculate extreme precipitation totals (Component 4) in the operational CEI come from daily data from the GHCN-Daily dataset (NCEI 2020; Menne et al. 2012). For the revised CEI, the data come from monthly climate division level values of the Climate Divisional Database (nCLIMDIV), version 2, dataset (Vose et al. 2014b).

Revising the CEI. The original and operational CEI incorporate five different components into the overall index. However, the authors mutually agreed with NCEI scientists that it would be acceptable to omit the fifth component (extremes in the number of days with recordable precipitation), while maintaining the scientific integrity of the CEI, for this purpose of demonstrating the utility of an Extremes Vulnerability Index.

Rather than basing each component on percentages of the country experiencing a certain extreme as the operational CEI does, Z scores (see above) were used to calculate the revised CEI. The Z score is used for each component to calculate the number of standard deviations of each component's monthly value from the 1981–2010 mean value, consistent with current literature (Actuaries Institute 2018). For Component 4, this method of calculating the Z score of the monthly total differs from the methodology of the operational CEI. Following Chebyshev's Rule, Z scores with an absolute value greater than 2 are considered for the purpose of this paper to be values that are “unusual,” and Z scores with absolute values greater than 3 are considered to be “extreme” values (see Table 1). The same Z-score threshold is considered to be extreme for all components; this leads to consistent analysis across all components and allows for the calculation of the final CEI to be on a numerical scale. The Z scores are now calculated for each component for each of the 344 climate divisions in the contiguous United States. Once the Z scores for each component were calculated, the numbers of extreme components per climate division were added together to calculate the final revised CEI value.

Results for the revised CEI versus the operational CEI.

To focus on the identification of extreme values and communication of information contained within the CEI, one month was chosen to use for comparison to the operational CEI. December 2015 was selected because a very strong El Niño event occurred during this winter. Many states in the southeastern United States recorded both temperature and precipitation values that were described as “well above normal,” making it both the warmest and wettest month on record for many reporting stations (NCEI 2016). Because the observed pattern consisted of warmer-than-normal temperatures *and* above-normal precipitation amounts, this month is abnormal for an El Niño event, which usually causes cooler-than-normal temperatures with above-normal precipitation in the Southeast (National Weather Service 2020). Using December 2015 data tests the hypothesis that Z scores will identify extreme values accurately but ignore non-extreme values.

The data for all CEI components for Decembers from the comparison period of 1981–2010 were used to compute the means and standard deviations employed in Chebyshev's Rule. December 2015 was compared to these Decembers via Chebyshev's rule, and three out of the four components for December 2015 were found to be unusual or extreme. In particular, Components 1 (maximum temperature), 2 (minimum temperature), and 4 (monthly precipitation totals) had a high percentage of Z scores falling at least two standard deviations above the mean (see Table 2). The only December 2015 component that was not unusual or extreme was Component 3 (PDSI).

CEI COMPONENT 1 (MAXIMUM TEMPERATURE). A comparison of the maps for the operational and revised CEI maximum temperature component reveals several differences (data from Esri 2010; NCEI 2018). The map from NCEI (Fig. 2) conveys the message that extremes in maximum temperature occurred in about half of the eastern United States, from Minnesota to Texas and eastward. However, the revised CEI (Fig. 3) shows that extreme values occurred in a much smaller portion of the country. Only New York's climate division 4, which consists of Long Island, exceeded the threshold with a Z score of 3.04.

Visually, comparison of these two maps demonstrates the effectiveness of Z scores at providing a more precise calculation of

Table 1. Interpretation of Z-score values.

Absolute value	Interpretation
0–2	Normal
2.01–3	Unusual
>3	Extreme

Table 2. Percentage of each December 2015 CEI component distribution lying within a number of standard deviations of the 1981–2010 mean.

CEI component	Percentage of Z scores lying within two standard deviations (%)	Percentage of Z scores lying within three standard deviations (%)
1	54.65	99.71
2	49.42	88.37
3	94.19	99.71
4	72.67	86.05

where statistically extreme values are occurring and how extreme these values are. Top and tail analysis, as currently used by NCEI to calculate the CEI, identifies a much larger portion of the United States that is extreme; in reality many of the locations highlighted as extreme in Fig. 2 experienced unusual (Z-score value between 2.01 and 3), but not extreme, conditions.

Fig. 2. December 2015 Component 1 map (courtesy of Karin Gleason, NCEI).

Fig. 3. Revised December 2015 CEI Component 1 values for all 344 climate divisions of the contiguous United States.

CEI COMPONENT 2 (MINIMUM TEMPERATURE). As with maximum temperature, the analysis of minimum temperature extremes using the revised CEI provides additional detail and a more accurate depiction of where extreme values occur. The operational CEI (Fig. 4) identifies warm minimum temperature extremes across the eastern two-thirds of the contiguous United States. In contrast, the revised CEI (Fig. 5) only identifies portions of the East Coast as having extreme values, generally from Georgia to Rhode Island. Most of the eastern half of the United States was unusual (Z scores between 2.01 and 3), but not extreme, for this component.

CEI COMPONENTS 3 AND 4 (MOISTURE AVAILABILITY AND MONTHLY PRECIPITATION). NCEI does not produce maps for these components, so there is currently no visual tool that can identify climate divisions with extreme PDSI values or monthly precipitation totals. However, the maps created based on values for the revised CEI provide users with information about how extreme each value is, and where the extremes are located (Figs. 6 and 7). The only PDSI value that is extreme for this month is located in Oklahoma's climate division 6, with a Z-score value of 3.18. This corresponds to a PDSI value for December 2015 of 2.91. Turning to monthly precipitation,

Fig. 4. December 2015 Component 2 map (courtesy of Karin Gleason, NCEI).

the state that had the highest concentration of extreme values in December 2015 was Iowa, with Z-score values across this state ranging from 3.07 to 3.51. The division that recorded the highest Z-score value for this month was Iowa's climate division 7, the southwestern-most climate division of the state. This Z score corresponds to a total monthly precipitation value for this division of 142.7 mm (5.62 in.).

OVERALL CEI. The four components of the revised CEI are combined into an overall index by simply adding the number of extreme components per climate division, per month, on a scale of 0 to 4. This is depicted for December 2015 in Fig. 8. While the majority of the United States did not have any extreme components during this month, there were six divisions that had two extreme components: climate division 4 in New York (Components 1 and 2), climate division 2 in Oklahoma (Components 3 and 4), climate division 5 in Georgia, climate divisions 4 and 5 in North Carolina,

and climate division 2 in South Carolina (Components 2 and 4 in each case). This fine-grained detail can have important implications when identifying potential risks associated with each extreme and also identifying populations that are vulnerable to being exposed to these extremes.

Fig. 5. Revised December 2015 CEI Component 2 values for all 344 divisions of the United States.

Fig. 6. Revised December 2015 CEI Component 3 values for all 344 divisions of the United States.

December 2015 CEI Component 4 (Monthly Precipitation Total) Z-scores

Fig. 7. Revised December 2015 CEI Component 4 values for all 344 divisions of the United States.

December 2015 CEI Values

Fig. 8. Revised December 2015 CEI values for all 344 divisions of the United States.

Social vulnerability: The Social Vulnerability Index (SVI)

The SVI from the CDC measures social vulnerability of each census tract in the United States (Flanagan et al. 2011). Overall social vulnerability to 15 different variables (including income, age, race, and housing conditions) is calculated by grouping variables into four

themes (Socioeconomic Status, Household Composition, Minority Status, and Housing and Transportation). A complete list of variables used and a description of the calculation of the SVI can be found in the SVI 2016 documentation (ATSDR 2017). The variables used come from census data; in order to calculate the index more frequently than every 10 years, estimated values from all variables included from the American Community Survey (ACS) are used to calculate the 2014 and 2016 index values.

Revising the SVI. To be able to combine the SVI with the revised CEI, the four SVI theme values (see Flanagan et al. (2011) for calculation information) were recalculated using Z scores. To make use of the most current data, values from the 2016 SVI were used. The Z score of the value of each theme for each county was calculated based on the national mean and standard deviation for the 2016 data. Then values were rescaled based on Z-score value so that they were on a numerical scale of only whole numbers, using a technique similar to Reid et al. (2009). Values used when rescaling are shown in Table 3. All values less than 0 were rescaled to 0 because in terms of vulnerability, negative numbers indicate areas that are more resilient.

Once values were rescaled, the values were summarized by maximum value per climate division using analysis tools within ArcMap. This was used to determine the impact of the highest amount of vulnerability in 2016 and identify all climate divisions that had counties that are highly vulnerable. To calculate the final SVI, the Z scores for each theme were added together, resulting in an index with a numerical scale ranging from 0 to 10. Higher values indicate a climate division that is more vulnerable.

Overall revised SVI values are shown in Fig. 9. The values were calculated by adding the Z-score values of each SVI theme per climate division together. The resulting index ranges from 0 (low vulnerability) to 10 (high vulnerability), due to the largest rescaled values per theme observed for 2016 data (3 for two themes, 2 for two themes). The areas of the United States with the highest levels of vulnerability, based on 2016 county-level data, are located in the southern and western United States. Almost all climate divisions in these regions had an overall SVI value of at least 7. Four climate divisions between these two regions had an overall SVI value of 10, meaning that these climate divisions had the highest rescored Z-score value possible for all themes. These climate divisions are climate division 9 in Texas, climate division 9 in Arkansas, climate division 6 in Alabama, and climate division 7 in South Carolina. These climate divisions are the most vulnerable based on 2016 ACS data; high vulnerability can be explained by high concentrations of low-income populations, children and disabled, minority populations, and mobile home communities.

Table 3. Rescaled values for the recalculated SVI.

Rescaled value	Corresponding Z-score values
0	<0
1	0–1
2	1.01–2
3	2.01–3

Calculation of the Extremes Vulnerability Index (EVI)

To calculate an index of extremes vulnerability, values from the revised CEI and SVI were combined to produce an overall value that indicates how vulnerable each climate division is and which index is contributing the most to overall vulnerability. To best communicate this, a bivariate scale was used. The advantage of using bivariate analysis is being able to identify both the level of physical exposure that each climate division faces and the preexisting conditions that can lead individuals living in these divisions to be vulnerable.

The values of each index were broken into three categories that correspond to low, medium, and high vulnerability. Values from each index included in each category are contained in Table 4. The different values included in each category of SVI vulnerability are based on the rescored Z-score values of each theme. The maximum Z-score value recorded per theme was either 2 or 3. This means that the highest SVI value a climate division could have is 10. This

2016 Social Vulnerability Index Total Maximum Values

Fig. 9. Overall maximum SVI values for 2016 data.

number gives an indication of the number of themes that had the highest possible Z-score value (per climate division). An SVI value between 0 and 3 indicates that a maximum of one theme per climate division recorded the maximum possible Z-score value. An SVI value between 4 and 6 indicates a maximum of two themes per climate division recording the highest possible Z score, and an SVI value between 7 and 10 indicates that three or four themes recorded the maximum Z-score value.

After creating different categories of vulnerability for each index, the values of both indices were paired to create a bivariate scale ranging from 1 to 9 to determine overall vulnerability. Bivariate scales are not additive, rather a comparison of the categories of values of two different variables. For this project, this scale indicates the level to which each climate division is vulnerable to variables included in each index, and also which index is impacting the overall value the most. An explanation of each value is contained in Table 5. A value of 9 indicates a climate division that is vulnerable to both physical exposure and social variables. A value of 1 indicates a climate division that is not highly vulnerable, and values between 2 and 7 indicate climate divisions that are moderately vulnerable to at least one factor. Using a scale of this type can help to identify the factors that each climate division is vulnerable to so that effective mitigation and adaptation strategies and policies can be implemented to decrease overall vulnerability.

Values of the EVI for December 2015 CEI values and 2016 SVI values are shown in Fig. 10. Classes 6, 8, and 9 indicate higher vulnerability, because this means that a climate division recorded a high value for at least one

Table 4. Values included in each group of vulnerability.

Vulnerability	CEI	SVI
Low	0	0–3
Medium	1–2	4–6
High	3–4	7–10

Table 5. Extremes Vulnerability Index interpretation.

EVI value	Interpretation
1	Low CEI value, Low SVI value
2	Medium CEI value, Low SVI value
3	High CEI value, Low SVI value
4	Low CEI value, Medium SVI value
5	Medium CEI value, Medium SVI value
6	High CEI value, Medium SVI value
7	Low CEI value, High SVI value
8	Medium CEI value, High SVI value
9	High CEI value, High SVI value

index. A value of 9 means that high levels of vulnerability were recorded for both indices, 8 means that a climate division had a high SVI value, and 6 indicates that the climate division recorded a high CEI value for that particular month.

In December 2015, two main regions of the United States were more vulnerable to the present climate extremes: the southeastern (from Alabama to Virginia) and the central United States (from Oklahoma through Missouri). All of the divisions included in these two regions had an EVI value of 8, indicating that the SVI value was high (between 7 and 10) and that they had a medium CEI value (either 1 or 2). Since the SVI value was ranked higher than the CEI value, this indicates that social variables are contributing to the overall vulnerability of these climate divisions slightly more than physical exposure.

Discussion and conclusions

Combining revised CEI and SVI values creates an Extremes Vulnerability Index (EVI) that for the first time calculates overall vulnerability to climate extremes by combining physical exposure and social demographic factors and demonstrates the level to which each index is impacting overall vulnerability. After comparing December 2015 CEI values and 2016 SVI values, two regions of the United States stand out as being the most vulnerable overall during a recent pronounced El Niño event: the southeastern United States and portions of the central United States. These regions both had a slightly higher vulnerability value from social factors than from physical exposure, but the bivariate scale indicates that physical exposure is still impacting overall vulnerability in these regions. Social factors that the CDC considers to be more vulnerable, contributing to overall vulnerability, include higher concentrations of low-income populations, higher percentages of children and disabled in these areas, higher concentrations of minority populations, and a high concentration of mobile homes. Pairing this information with higher exposure to climate extremes identifies communities that are less equipped to respond, and thus more vulnerable, to climate extremes. This information can be used and applied by policy-makers to create and implement policies that help to increase

Extremes Vulnerability Index for December 2015

Fig. 10. EVI values for December 2015 CEI and 2016 SVI.

resilience in these climate divisions and mitigate overall vulnerability. In real time, using the EVI to determine areas that have the most vulnerable populations can also be used to distribute resources and aid most effectively when an extreme event occurs.

An additional benefit of using the EVI is that it can help to indicate potential health risks to vulnerable climate divisions. Since maximum and minimum temperatures across the vulnerable divisions of the southeastern United States were higher than normal, with many of these areas recording extreme warm minimum temperatures for December 2015, these climate divisions could be more susceptible to vector-borne diseases that require warm conditions to spread. For example, higher minimum temperatures and increased precipitation create an environment favorable for the growth of the *Aedes aegypti* mosquito (Christophers 1960), the mosquito that carries the Zika virus. In 2016, there was an increase in the number of Zika cases reported in the United States, and many states in the Southeast recorded high numbers of cases (CDC 2019). Using a combined index like the EVI to identify regions that are the most vulnerable to diseases like this can be instrumental in the development of effective warning strategies by health professionals or emergency managers.

There are several conclusions that can be taken from this project.

- 1) Using Z scores is an accurate and effective way to identify extreme values within a dataset. For any dataset, normally distributed or not, interpreting this statistic using Chebyshev's Rule emphasizes the mathematical relationship between the mean, the standard deviation, and the rest of the data. This means that one can quantify the amount by which a certain data point deviates from the mean of a dataset, rather than merely knowing it is in the top or bottom 10% of the data.
- 2) Calculating the CEI for each climate division of the United States allows for a relatively localized index calculation and creates a more useful tool for the general public. This can be seen in the maps created for December 2015 CEI values. Using these maps allows for the user to see exactly where the extreme values were located, as well as compare those extreme values to the value in their own division to determine whether or not their division was extreme for a given component in a given month.
- 3) After combining revised CEI and SVI values, we have created an Extremes Vulnerability Index that for the first time calculates overall vulnerability to climate extremes by combining physical exposure and social demographic factors and demonstrates the level to which each index is impacting overall vulnerability. Information from this index can be used and applied by policy-makers to create and implement policies that help to increase resilience in these climate divisions and mitigate overall vulnerability. The EVI also has the potential to indicate potential health risks to vulnerable climate divisions. Being able to reference this crucial information can help health professionals create effective warning strategies and materials.

There are many opportunities for future work for this project, including operationalizing the EVI and recalculating the fifth component of the CEI so that the revised CEI contains all five original components. We are also interested in applying this research to communities outside the United States. Making use of daily, as opposed to monthly data, to analyze vulnerability to the temporal duration of extreme temperature events is another opportunity for future work.

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Data Availability Statement. SVI, climate division shapefile, map layer, and precipitation data were all downloaded from public resources cited in this article's Reference section.

CEI data and source can be made available upon request. Please contact NCEI's Monitoring Section at ncei.monitoring.info@noaa.gov for additional information.

References

- AAA, CIA, CAS, and SAC, 2016: Actuaries climate index: Executive summary. American Academy of Actuaries, Canadian Institute of Actuaries, Casualty Actuarial Society and Society of Actuaries, accessed January 2018, <http://actuariesclimateindex.org>.
- Actuaries Institute, 2018: Australian actuaries climate index: Design documentation. Accessed January 2019, <https://actuaries.asn.au/microsites/climate-index>.
- Allison, E. H., and Coauthors, 2009: Vulnerability of national economies to the impact of climate change on fisheries. *Fish. Fish.*, **10**, 173–196, <https://doi.org/10.1111/j.1467-2979.2008.00310.x>.
- ATSDR, 2017: Social vulnerability index 2016 database US. Agency for Toxic Substances and Disease Registry, CDC, accessed February 2019, <https://svi.cdc.gov/data-and-tools-download.html>.
- Bell, J. E., 2018: Double threat. *The Actuary Magazine*, April/May 2019, accessed June 2018, <https://theactuarymagazine.org/double-threat/>.
- CDC, 2019: Zika virus. Centers for Disease Control and Prevention, accessed 25 March 2019, www.cdc.gov/zika/reporting/2016-case-counts.html.
- Christophers, S. S. R., 1960: *Aedes Aegypti (L.)*, *The Yellow Fever Mosquito*. Cambridge University Press, 739 pp.
- Crimmins, A., and Coauthors, Eds., 2016: The impacts of climate change on human health in the United States: A scientific assessment. U.S. Global Change Research Program, 312 pp., <http://doi.org/10.7930/JOR49NQX>.
- Cutter, S. L., B. J. Boruff, and W. L. Shirley, 2003: Social vulnerability to environmental hazards. *Soc. Sci. Quart.*, **84**, 242–261, <https://doi.org/10.1111/1540-6237.8402002>.
- Esri, 2010: USA major lakes layer file. Esri_dm, accessed November 2018, www.arcgis.com/home/item.html?id=ddf2ddc54868482fb7eb4c09d658f960.
- Flanagan, B. E., E. W. Gregory, E. J. Hallisey, J. L. Heitgerd, and B. Lewis, 2011: A social vulnerability index for disaster management. *J. Homeland Secur. Emerg. Manage.*, **8**, 3.
- Gallant, A. J. E., and D. J. Karoly, 2010: A combined climate extremes index for the Australian region. *J. Climate*, **23**, 6153–6165, <https://doi.org/10.1175/2010JCLI3791.1>.
- Gleason, K. L., J. H. Lawrimore, D. H. Levinson, and T. R. Karl, 2008: A revised U.S. climate extremes index. *J. Climate*, **21**, 2124–2137, <https://doi.org/10.1175/J2007JCLI1883.1>.
- Gopal, P., 2019: America's great climate exodus is starting in the Florida Keys. Bloomberg.com, accessed 2 October 2019, www.bloomberg.com/news/features/2019-09-20/america-s-great-climate-exodus-is-starting-in-the-florida-keys.
- IPCC, 2007: *Climate Change 2007: Impacts, Adaptation and Vulnerability*. M. L. Parry et al., Eds., Cambridge University Press, 976 pp.
- , 2014: *Climate Change 2014: Synthesis Report*. R. K. Pachauri et al., Eds., IPCC, 151 pp., www.ipcc.ch/report/ar5/syr/.
- Karl, T. R., R. W. Knight, D. R. Easterling, and R. G. Quayle, 1996: Indices of climate change for the United States. *Bull. Amer. Meteor. Soc.*, **77**, 279–292, [https://doi.org/10.1175/1520-0477\(1996\)077<0279:IOCCFT>2.0.CO;2](https://doi.org/10.1175/1520-0477(1996)077<0279:IOCCFT>2.0.CO;2).
- KC, B., J. M. Shepherd, and C. J. Gaither, 2015: Climate change vulnerability assessment in Georgia. *Appl. Geogr.*, **62**, 62–74, <https://doi.org/10.1016/j.apgeog.2015.04.007>.
- Larson, R., and B. Farber, 2006: *Elementary Statistics: Picturing the World*. Pearson Prentice Hall, 615 pp.
- Menne, M. J., I. Durre, R. S. Vose, B. E. Gleason, and T. G. Houston, 2012: An overview of the global historical climatology network-daily database. *J. Atmos. Oceanic Technol.*, **29**, 897–910, <https://doi.org/10.1175/JTECH-D-11-00103.1>.
- National Weather Service, 2020: El Nino and its effect on southeast U.S. weather. Accessed May 2020, www.weather.gov/tae/enso.
- NCEI, 2016: State of the climate: National climate report for December 2015. Accessed 7 March 2019, www.ncdc.noaa.gov/sotc/national/201512.
- , 2018: Climate division shapefiles. Earth System Research Laboratory, accessed November 2018, <https://psl.noaa.gov/data/usclimdivs/boundaries.html>.
- , 2020: U.S. Climate Extremes Index (CEI). Accessed 7 March 2019, www.ncdc.noaa.gov/extremes/cei/data-used.
- Owen, R., 2019: Actuaries are paying attention to climate data [in “Explaining Extremes of 2017 from a Climate Perspective”]. *Bull. Amer. Meteor. Soc.*, **100** (1), S5–S8, <https://doi.org/10.1175/BAMS-D-18-0293.1>.
- Oxfam America, 2018: Mapping social vulnerability in Southeastern states and the Gulf Coast. Accessed 16 March 2018, <https://policy-practice.oxfamamerica.org/work/poverty-in-the-us/mapping-social-vulnerability-in-southeastern-states-and-the-gulf-coast/>.
- Palmer, W. C., 1965: Meteorological drought. U.S. Weather Bureau Research Paper 45, 58 pp., www.ncdc.noaa.gov/temp-and-precip/drought/docs/palmer.pdf.
- Peltz, J., 2019: ‘Survive, not enjoy’: Heat, humidity gripping half the US. *Associated Press*, 20 July, accessed 3 October 2019, <https://apnews.com/fe99dd4effcf4e8a9263c41b51509c5e>.
- Portier, C. J., and Coauthors, 2010: A human health perspective on climate change: A report outlining the research needs on the human health effects of climate change. Environmental Health Perspectives/National Institute of Environmental Health Sciences, 70 pp., www.niehs.nih.gov/health/materials/a_human_health_perspective_on_climate_change_full_report_508.pdf.
- Reid, C. E., M. S. O'Neill, C. J. Gronlund, S. J. Brines, D. G. Brown, A. V. Diez-Roux, and J. Schwartz, 2009: Mapping community determinants of heat vulnerability. *Environ. Health Perspect.*, **117**, 1730–1736, <https://doi.org/10.1289/ehp.0900683>.
- Reidmiller, D. R., Eds., 2018: *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment*. Vol. II, U.S. Global Change Research Program, 1515 pp., <https://doi.org/10.7930/NCA4.2018.CH1>.
- Shafer, D., and Z. Zhang, 2017: Descriptive statistics. *Introductory Statistics*, LibreTexts, [https://stats.libretexts.org/Textbook_Maps/Map%3A_Introductory_Statistics_\(Shafer_and_Zhang\)/02%3A_Descriptive_Statistics/2.5%3A_The_Empirical_Rule_and_Chebyshev's_Theorem](https://stats.libretexts.org/Textbook_Maps/Map%3A_Introductory_Statistics_(Shafer_and_Zhang)/02%3A_Descriptive_Statistics/2.5%3A_The_Empirical_Rule_and_Chebyshev's_Theorem).
- Vose, R. S., and Coauthors, 2014a: Improved historical temperature and precipitation time series for U.S. climate divisions. *J. Appl. Meteor. Climatol.*, **53**, 1232–1251, <https://doi.org/10.1175/JAMC-D-13-0248.1>.
- , and Coauthors, 2014b: NOAA's gridded Climate Divisional Dataset (CLIMDIV), version 2. NOAA National Centers for Environmental Information, accessed December 2018, <https://doi.org/10.7289/V5M32STR>.
- Wilks, D. S., 1989: Rainfall intensity, the Weibull distribution, and estimation of daily surface runoff. *J. Appl. Meteor.*, **28**, 52–58, [https://doi.org/10.1175/1520-0450\(1989\)028<0052:RITWDA>2.0.CO;2](https://doi.org/10.1175/1520-0450(1989)028<0052:RITWDA>2.0.CO;2).