Graphical Abstract

The effect of heterogeneous severe drought pattern on all-cause and cardiovascular mortality in the Northern Rockies and Plains of the United States

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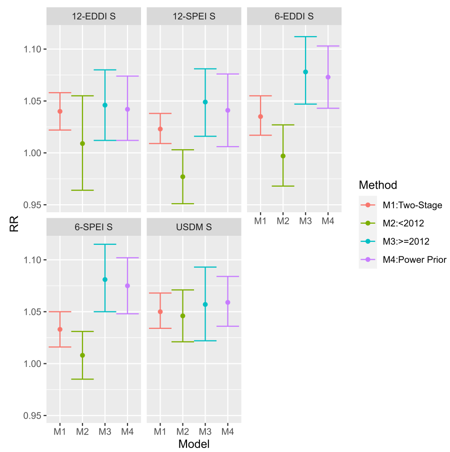

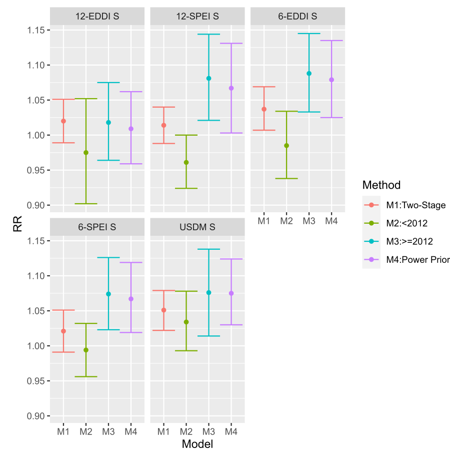

Highlights

The effect of heterogeneous severe drought pattern on all-cause and cardiovascular mortality in the Northern Rockies and Plains of the United States

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- This is the first drought-related health impact study to properly accommodate heterogeneous pattern of severe drought.
- Severe drought increased the risk ratios of mortalities and these associations are statistically significant.
- A mid-term (6-month) severe drought had higher risk ratios of mortalities in the general population of the Northern Rockies and Plains.

The effect of heterogeneous severe drought pattern on all-cause and cardiovascular mortality in the Northern Rockies and Plains of the United States

Yeongjin Gwon[a,f], Richard Nagaya[a], Yuanyuan Ji[a], Azar M. Abadi[b], Austin Rau[c], Jesse D. Berman[c], Ronald D. Leeper[d], Jared Rennie[d], Jesse E. Bell[e,f,g]

[a]*Department of Biostatistics, College of Public Health, University of Nebraska Medical Center, Omaha, 68198, Nebraska, USA*
[b]*Environmental Health Sciences, School of Public Health, University of Alabama, Birmingham, 35233, Alabama, USA*
[c]*Division of Environmental Health Sciences, School of Public Health, University of Minnesota, Minneapolis, 55455, Minnesota, USA*
[d]*North Carolina Institute for Climate Studies, North Carolina State University, Raleigh, 27695, North Carolina, USA*
[e]*Department of Environmental, Agriculture, Occupational and Health, University of Nebraska Medical Center, Omaha, 68198, Nebraska, USA*
[f]*Daugherty Water for Food Global Institute, University of Nebraska, Lincoln, 68588, Nebraska, USA*
[g]*School of Natural Resources, University of Nebraska, Lincoln, 68588, Nebraska, USA*

Abstract

Drought is a distinct and complicated climate hazard that regularly leads to severe economic impacts. Changes in the frequency and occurrence of drought due to anthropogenic climate change can lead to new and unanticipated outcomes. To better prepare for health outcomes, more research is needed to develop methodologies to understand potential consequences. This study suggests a new methodology for assessing the impact of monthly severe drought exposure on mortality in the Northern Rockies and Plains of the United States from 2000 to 2018. A two-stage model with the power prior approach was applied to integrate heterogeneous severe drought pattern and estimate overall risk ratios of all-cause and cardiovascular mortality related to multiple drought indices (the US Drought Monitor, 6- and 12-month Standardized Precipitation-Evapotranspiration Index, 6- and 12-month Evaporative Demand Drought Index). Under severe drought, the risk ratios of all-cause mortality are 1.059 (95% Cr: 1.036 to 1.084, USDM), 1.075 (95% Cr: 1.048 to 1.102, 6-SPEI), 1.041 (95% Cr: 1.006 to 1.076, 12-SPEI), 1.073 (95% Cr: 1.043 to 1.103, 6-EDDI), and 1.042 (95% Cr: 1.012 to 1.074, 12-EDDI); cardiovascular mortality are 1.075 (95% Cr: 1.030 to 1.124, USDM), 1.067 (95% Cr: 1.019 to 1.119, 6-SPEI), 1.067 (95% Cr: 1.003 to 1.131, 12-SPEI), 1.079 (95% Cr: 1.025 to 1.135, 6-EDDI), and 1.009 (95% Cr: 0.959 to 1.062, 12-EDDI). Our results showed that (i) a model with properly accounted for heterogeneous exposure pattern had greater risk ratios; and (ii) a mid-term (6-month) severe drought had higher risk ratios compared to longer-term (12-month) drought. These results expand the existing knowledge of drought relationship to increasing mortality in the United States. The findings from this study highlight the need for communities and policymakers to establish effective drought-prevention initiatives in this region.

Keywords: All-cause mortality, cardiovascular mortality, climate change, drought, risk ratio, power prior, public health

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1. Introduction

Drought is one of the costliest climate-related disasters in the United States (Bell et al., 2018). The threat of drought is increasing due to anthropogenic climate change (Hoegh-Guldeberg et al., 2018). Due to changes in the physical environment associated with droughts, there are a range of sectors that are affected, including human health, human communities, natural resources, and ecosystems (Bell et al., 2018, 2016; Field et al., 2014). Despite considerable public health concerns, the assessment of health risks associated with drought exposure is frequently disregarded in the United States, particularly in regional-based assessments (Fard et al., 2022). One potential explanation of the lack of research is the complexity of linking drought to health outcomes. Drought lacks the direct pathway to health outcomes like many other climate-related events. In addition, multiple drought indices showed a distinct pattern in capturing drought episodes in the same geographical location (Gwon et al., 2023). To address these issues, more research is needed on region-based or region-specific disparities to understand how and why they differ.

A substantial number of epidemiological studies have been conducted in the previous decade to investigate the potential link between drought exposure and mortality. The majority of studies in the United States found that severe drought, rural communities, and elderly populations over 65 years old were at a higher risk of all-cause, cardiovascular, or respiratory mortality (Berman et al., 2017, 2021; Lynch et al., 2020; Abadi et al., 2022; Gwon et al., 2023). In particular, the areas that experience drought less frequently were more sensitive and had higher mortality risks compared to areas that chronically experience drought conditions (Berman et al., 2017; Gwon et al., 2023). Several studies in Spain, Portugal, and Brazil had similar assessment and showed that longer-term drought and extended drought periods increased daily mortality risk for the elderly individuals (Salvador et al., 2019, 2020b, 2021, 2022). Other studies suggested that short-term drought with high temperature and air pollution had negatively impact on the selected cause of mortality (Salvador et al., 2020a,c). In the Northernmost region of Bangladesh, short-term extreme drought increased the risk of natural cause, cardiovascular, respiratory disease (Alam et al., 2021, 2022). All these results provided extensive analysis and significant findings using standard time-series modeling approach that is common in environmental epidemiology.

One of the most difficult aspects of modeling time-series data is integrating trends of heterogeneous exposure over the study period. We frequently observe in climate- or weather-related health risk assessments that such exposure shows a rapid spike or slab at a certain time-point or time-window due to unanticipated circumstances. The 2012 drought in the United States caused around $30 billion in damage (Smith and Katz, 2013) and was one of the most severe and damaging droughts in recent history since the Dust Bowl of the 1930s (Basara et al., 2013). Although the drought of 2012 spread across most of the United States, it mainly affected the Midwest and Great Plains regions (Peterson et al., 2013; Hoerling et al., 2013; Bell et al., 2018). The impact on health outcomes would be biased if this heterogeneous exposure trend was not appropriately accounted for, or the magnitude of the effect would be underestimated or disguised. This has provided a scientific motivation for the development of an adequate statistical model in assessing health risks associated with climate- or weather-related exposure.

The power prior discussed by Ibrahim and Chen (2000) has emerged as a useful class of informative priors in Bayesian inference when historical data are available. This approach is a potential statistical solution to integrate heterogeneous datasets. The main idea is to determine how much of the past data will be used in the present data. It has broad applications in a variety of fields, including health care, clinical trials, economics, and business (Ibrahim et al., 2015). In a water quality evaluation, water segment impairment tests using the power prior had greater power than the raw score approach used by the Environmental Protection Agency (EPA) to determine the percentage of samples in violation of the water quality standard (Duan et al., 2006). In toxicology, power prior approach was superior to find dose-response relationship and also successfully achieved the reduction of the uncertainty in benchmark dose estimation (BMD) (Shao, 2012, 2011). Moreover, Chen and Ibrahim (2004) applied the power prior to predict daily-level ragweed pollen in Kalamazoo, Michigan, from 1991 to 1994. Within the daily-level correlated time-series data, they considered the data 1991 to 1992 as historical data, the data 1993 as the current data, and the data 1994 as validation data to predict pollen level.

In this article, we propose a new methodology to estimate the overall risk ratios of all-cause and cardiovascular mortalities associated with the drought exposure. We are particularly interested in investigating the impact of severe drought on health outcomes because there is a distinct trend of severe drought prior to and after 2012 (See Figure 2 in Section 4.2). To the best of our knowledge, this is the first drought-related health study to properly incorporate heterogeneous exposure pattern. The outcomes of the current study support the hypothesis that severe drought increases mortality risk ratios in the general population of the Northern Rockies and Plains. Our findings will contribute to a better understanding of the impacts of heterogeneous exposure in the assessment of health risks.

2. Materials

2.1. Study Area: Northern Rockies and Plains

The Northern Rockies and Plains region of the United States encompasses five states: Montana, Wyoming, North Dakota, South Dakota, and Nebraska. The region is characterized by the Rocky Mountains in the west and experiences a diverse range of climate due to geographical distinction. Furthermore, a majority of the territory is known for large-scale agriculture and cattle ranching, which are the region's principal sources of income. Rural communities make up 88.3% of the counties (Ingram and Franco, 2013) and the Great Plains where is the eastern part of the region and were the most affected by the severe drought of 2012 (Peterson et al., 2013; Hoerling et al., 2013). Furthermore, the climate scenarios are projecting an increase in frequency and severity of drought in this region (Zambreski et al., 2018). This information qualifies the region as an excellent study location.

2.2. Health Data

We extracted mortality data from the National Center for Health Statistics (NCHS) from January 2000 to December 2018. Using the data, we generated monthly county-level death counts for cardiovascular disease (ICD-10 codes I00-I99) and for all-cause mortality in the Northern Rockies and Plains of the United States. The datasets were stratified these counts by monthly aggregations into four age groups (0-19, 20-39, 40-64, and over 65 years), three race groups (White, Black, and other than white and black), and sex (male and female). The annual county-level population by demographic variables (age, gender, and sex) were obtained from the surveillance, epidemiology, and end results (SEER) program (National Cancer Institute, 2021) and these estimates were used in all the months in each calendar year. The final datasets was aggregated by the demographic variables to compute monthly county-level death counts of cardiovascular and all-cause mortalities for the total population.

2.3. Climate Data

2.3.1. The United States Drought Monitor (USDM)

The USDM is a collaborative effort between the National Oceanic Atmospheric Administration (NOAA), the U.S. Department of Agriculture (USDA), and the National Drought Mitigation Center (NDMC) that has been providing weekly updates of drought conditions since 2000 (Svoboda et al., 2002). Using a convergence of evidence approach, drought authors blend moisture deficits from across the hydrological cycle (i.e., precipitation, soil moisture, evaporation, etc) with drought reports from local experts to categorize drought conditions into one of six categories: wet to normal conditions (None), abnormally dry (D0), moderate (D1), severe (D2), extreme (D3), and exceptional (D4). We then reclassified USDM measures into monthly binary and three-level categories for this assessment. A binary measure was estimated based on the frequencies of the drought status within a given month and county. 'No drought' was defined if the frequencies of no drought and D0 condition in the week within a given month and county has more than the frequencies for all D1 to D4 conditions. Otherwise, it is labeled as a drought condition. The three-level categorical status is determined as (i) no drought in the binary measure; (ii) moderate drought (with binary drought condition and the sum of frequencies of D1 and D2 are greater than that of D3 and D4); and (iii) severe drought (with binary condition and the sum of frequencies of D3 and D4 are greater than that of D1 and D2).

2.3.2. The Standardized Precipitation-Evapotranspiration Index (SPEI)

The SPEI has been well-accepted in drought research including studies on health impacts globally (Lynch et al., 2020; Salvador et al., 2019, 2020b, 2021, 2022). The SPEI has a various time scale (weekly to monthly) and is calculated using precipitation and temperature measurements, as well as the balance of precipitation and evapotranspiration (Vicente-Serrano et al., 2010). The index is a standardized continuous value with positive values indicating wet conditions and negative values indicating dry conditions (drought). We use the SPEI at 6-month and 12-month accumulation in this study as a proxy for medium- and long-term drought. The resulting 6- and 12-month SPEI value represents the degree of wetness or dryness of the past 6- and 12-month relative to the historical reference period. Although SPEI is a continuous value, it can be categorized mirrored to the same classes of USDM that support equivalent comparison between USDM and SPEI drought conditions (Svoboda et al., 2002).

2.3.3. Evaporative Demand Drought Index (EDDI)

The EDDI measures drought signals by assessing how atmospheric evaporative demand (E0) responds to surface drying anomalies (Hobbins et al., 2016; McEvoy et al., 2016). This index provides near-real-time information for the entire U.S. and is available in various timescales from weekly through monthly. Short-term EDDI, for example, indicates the atmospheric conditions that can lead to flash droughts, while longer-term EDDI may indicate the development of more sustained drought conditions. Similar to the SPEI, EDDI is a continuous value and can be categorized with the same categories in USDM that are determined based on the distribution of aggregated evaporative demand values (Hobbins et al., 2016; McEvoy et al., 2016). This supports equivalent comparison between USDM and EDDI drought estimates.

2.3.4. Temperature Anomaly

A monthly mean temperature was included from the NOAA's Nclimgrid product at a 5km grid cell resolution (Vose et al., 2022). We then calculated a monthly county level temperature anomaly as the difference between the mean monthly temperature and the 30-year mean monthly temperature from 1991-2020 using zonal averages of all grid cells falling within a county boundary.

3. Statistical Modeling

3.1. Power Prior

The Power power prior is a useful class of informative prior to integrate a certain level of historical data D_H to the current data D_C in Bayesian inference (Ibrahim and Chen, 2000; Ibrahim et al., 2015). The elicitation of the power prior is based on the historical data and a discounting parameter a_0 that quantifies the similarity (or heterogeneity) between current data and historical data. A large value of a_0 represents high degree of similarity between two datasets, while small value indicates the opposite. The parameter a_0 also controls the influence of the historical data on the current data and is restricted to be between 0 and 1, $0 \leq a_0 \leq 1$. No historical data is incorporated if $a_0 = 0$, while full historical data is accommodated when $a_0 = 1$. The value of a_0 is often chosen based on a statistical criterion for computational simplicity (Ibrahim et al., 2015). We treat it as a random quantity, however, by specifying its proper prior distribution. This allows the data to determine the value of a_0.

3.2. Two-stage Model

We used a two-stage model to estimate county-level and overall risk ratio of all-cause mortality associated with drought exposure. First, we divided the dataset into two sub-datasets: prior to and after 2012. The sub-data before 2012 was considered as the historical data and the data after 2012 was used as the current data. This threshold was determined based on the mean percentage of the severe drought episodes in Figure 2.

In the first stage, a separate quasi-Poisson regression model was used to estimate location-specific risk ratios in historical data and current data. We included cubic B-spline of month with 7 degrees of freedom to control long-term time trend, second degree polynomial of anomaly temperature, and indicator variables to control calendar year effect. The drought exposure, moderate and severe drought, were used as categorical variables (No drought as a reference level). The values of logarithm for population size in each county were used an offset variable in the model.

In the second stage, we applied Bayesian meta regression to estimate the overall risk ratio. Specifically, we combined county-specific risk ratio by a random effect Bayesian linear regression model with power prior approach to evaluate the overall risk ratio. We performed the entire analysis using

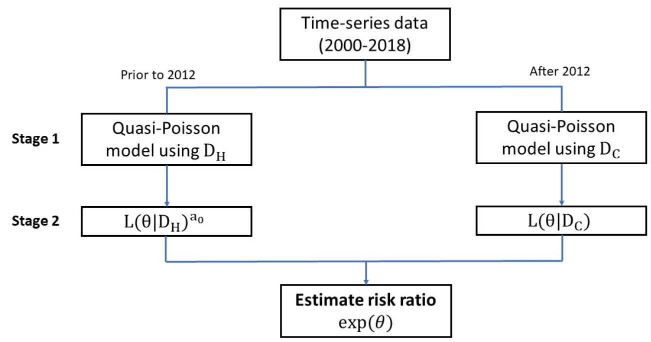

Figure 1: Flow of the diagram of the proposed statistical modeling. Note that $L(\theta|D_H)$ and $L(\theta|D_C)$ are likelihood functions of the second stage model, respectively. Moreover, θ is the risk ratio at logarithm scale.

two-stage model with power prior approach. We note that the model formulation in the first stage leads to the county-specific estimates that are being interpreted as the county-level risk ratio at logarithm scale. Therefore, we considered the impacts at an exponential to compute the overall risk ratio in the second stage. Weakly non-informative priors were used on the regression coefficient $\theta \sim N(0, 100)$ and discounting parameter $a_0 \sim Beta(1, 1)$. We considered the impacts at an exponential to compute the overall risk ratio due to the model formulation and its interpretation of the risk ratio at the log-scale. Figure 1 displays the flow of diagram of our proposed statistical modeling. Note that details on the power prior and its formulation can be found in Section S1 of the Supplementary Materials.

In all Bayesian computations, we used 50,000 Markov Chain Monte Carlo (MCMC) samples after a burn-in of 10,000 iterations to compute the posterior summaries, including posterior means, posterior standard deviations, and 95% Credible Intervals (Cr). The convergence of the Gibbs sampler was examined by trace plots and auto-correlation plots. Statistical significance is determined if the 95% Cr of the estimated risk ratios do not include the value of one. The R statistical software (version 4.2.2) was used to generate all figures. For all statistical analyses, Statistical Analysis Software (SAS version 14.2) with PROC GLIMMIX and PROC MCMC procedures was used.

4. Results

4.1. Descriptive Statistics

Table 1 provides summary statistics for all-cause and cardiovascular death outcomes in the Northern Rockies and Plains during the 2000-2018. The total number of all-cause and cardiovascular deaths were 813,121 and 256,029, respectively. As observed in all population in the region, the variability of the death counts exceeds the mean death counts ($366.22^2 > 3566.32$ and $115.36^2 > 1122.93$ for all-cause and cardiovascular, respectively), indicating that there is overdispersion in the mortality data. This demonstrates that the overdispersed quasi-Poisson distribution is a good fit for the distribution of death counts. Nebraska had the highest observed mean mortality rates (1313.60 and 413.79 in all-cause and cardiovascular mortality, respectively), accounting for nearly 37% of all deaths. Wyoming has the lowest percentage of both mortality occurrences in the region, less than 10%. In the order and magnitude, five states in the region showed the same death rate trends (See Table 1).

Table 1: Baseline characteristics of study populations by state during study period (2000-2018). N is the number of cause-specific deaths, n is the number counties in the state, and SD indicates standard deviation.

Region	County	**All-cause**			**Cardiovascular**		
	n	N	Mean	SD	N	Mean	SD
Total	291	813,121	3566.32	366.22	256,029	1122.93	115.36
Montana	56	170,495 (20.97%)	749.79	24.63	50,657 (19.79%)	228.13	7.30
Wyoming	23	78,256 (9.62%)	343.23	16.71	23,221 (9.07%)	101.85	4.86
North Dakota	53	123,809 (15.23%)	543.02	21.42	41,047 (16.03%)	180.03	6.69
South Dakota	66	141,060 (17.35%)	618.68	22.17	46,759 (18.26%)	205.08	6.64
Nebraska	93	299,501 (36.83%)	1313.60	44.95	94,345 (36.86%)	413.79	12.98

Table 2 summarizes the monthly frequency of total drought exposure in the Northern Rockies and Plains. The frequency was accumulated if the counties were experienced binary, moderate, or severe drought during the study period. Overall, the USDM captured more drought events (approximately 34.3%) than the SPEI (25.8% for 6-month and 28.7% for 12-month) and EDDI (26.8% for 6-month and 28.7% for 12-month).

Figure 2 displays the average percentage of the drought having binary, moderate, and severe drought events with varying drought exposures during the study period. The average percentage was calculated using the total

Table 2: Baseline characteristics for the county-months frequency of different drought exposure levels by different drought indices during study period (2000-2018). Abbreviations indicate the drought indices (USDM=U.S. Drought Monitor, SPEI=Standardized Precipitation-Evapotranspiration Index, EDDI=Evaporative Drought Demand Index) and the monthly frequencies of drought.

Drought	USDM	6-SPEI	12-SPEI	6-EDDI	12-EDDI
None	43,575 (65.7%)	49,253 (74.2%)	47,328 (71.3%)	48,578 (73.2%)	47,271 (71.3%)
Moderate	16,597 (25.0%)	13.391 (20.2%)	14,382 (21.7%)	13,224 (19.9%)	14.407 (21.7%)
Severe	6176 (9.3%)	3704 (5.6%)	4638 (7.0%)	4546 (6.9%)	4670 (7.0%)

number of drought episodes in the counties with binary, moderate, and severe drought over the full study period. Year after year, quite different temporal patterns of binary and moderate drought were observed. Except for the year 2012, the severe drought followed a similar pattern. In 2012, the 6-month and 12-month EDDI showed that the majority of the drought was severe (78.8% for 6-month and 72.2% for 12-month), whereas the 6-month and 12-month SPEI captured both moderate and severe drought in a similar way (See Figure 2). This pattern clearly showed that the health risk associated with the severe drought exposure will differ prior to and after 2012. If varied temporal patterns are not appropriately addressed, the effect of drought on health outcomes may be masked or underestimated. To estimate the overall risk ratio of all-cause and cardiovascular mortality, we need to consider either two separate analyses prior to and after 2012 or develop a new statistical model.

4.2. Association between severe drought exposure and mortalities

While our proposed methodology is equally applicable to the binary drought classification and the moderate drought category, we are mainly reporting results based on severe drought in this article. We performed four different analyses based on usual two-stage model (M1), two-stage model with separate analyses prior to (M2) and after 2012 (M3), and two-stage model with power prior approach (M4) to evaluate the overall risk ratio of all-cause and cardiovascular mortality associated with different drought exposures.

We included counties in the second stage modeling fitting if the estimate of drought exposure was between -1.5 and 1.0 and the standard error was less than 1.0 on a logarithmic scale (Gwon et al., 2023). This suggests to an estimated location-specific risk ratio of 0.22 to 2.72, which is acceptable in practice. Because the majority of counties were rural, almost 10% were

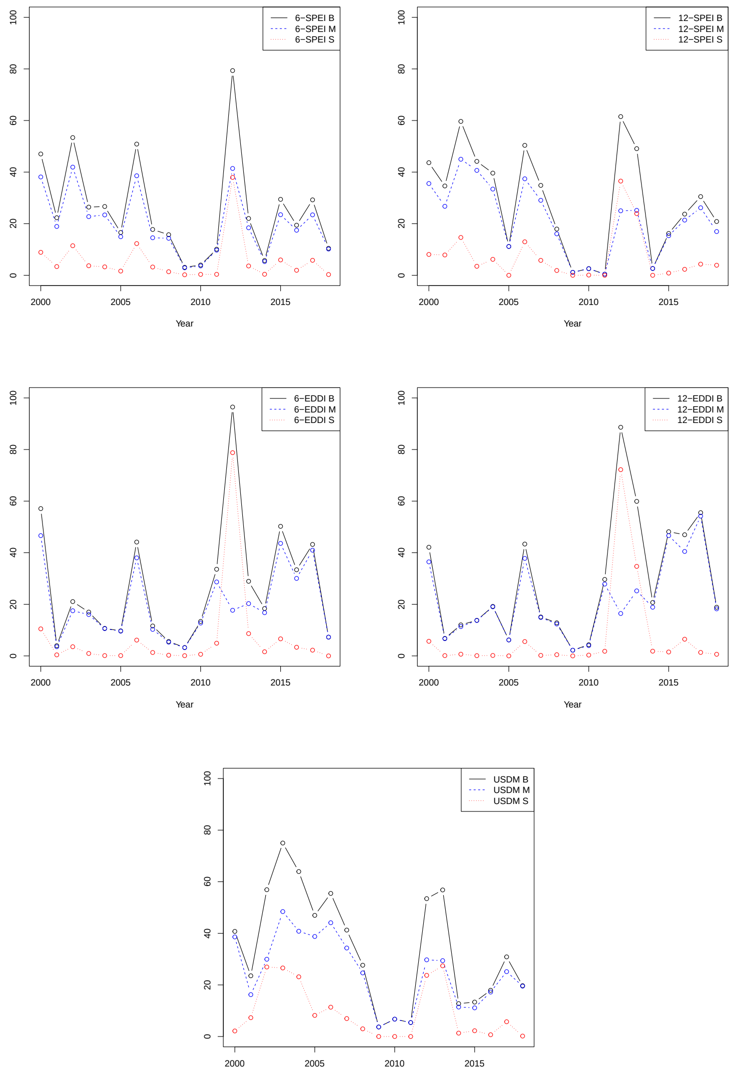

Figure 2: The percentage of months exposed to drought events (binary, moderate, and severe) using two drought indicators with different timescales by the Northern Rockies and Plains of the United States from 2000 to 2018. Abbreviations indicate drought events (B: binary, M: moderate, S: severe) and drought indices (SPEI=Standardized Precipitation-Evapotranspiration Index, EDDI=Evaporative Drought Demand Index, USDM=United States Drought Monitor).

included in the analysis if typical population size was used as an inclusion criterion to limit model convergence (just 37 out of 291 counties if more than 5,000 was included). However, our approach assured that more than 75% of counties were included in the second stage, resulting in increased statistical power across all regions.

Figure 3 shows the posterior estimates and their corresponding 95% Crs of the estimated overall risk ratios by four different analyses (M1 to M4). Results from the second stage model show that the overall risk ratios differed in direction and magnitude by different methods. In the usual two-stage model (M1), there were positive associations between all-cause mortality and different severe drought exposures. The region had statistically significant all-cause mortality risk ratios of 1.050 (95% Cr: 1.034 to 1.068), 1.033 (95% Cr: 1.016 to 1.050), 1.023 (95% Cr: 1.009 to 1.038), 1.035 (95% Cr: 1.017 to 1.055), and 1.040 (95% Cr: 1.022 to 1.058) by USDM, 6-month SPEI, 12-month SPEI, 6-month EDDI, and 12-month EDDI, respectively. The result showed that the USDM increased the risk ratio by 5.0% and other drought exposures were interpreted similarly. However, only the USDM and 6-month EDDI had statistically significant cardiovascular mortality risk ratios of 1.051 (95% Cr: 1.022 to 1.079) and 1.037 (95% Cr: 1.007 to 1.069). This indicates that the USDM and 6-month EDDI increased the risk ratio by 5.1% and 3.7%, respectively. Note that all posterior estimates and the value of a_0 under M1 to M4 are presented in Tables S1 and S2 of the Supplementary Materials.

The results by separate analyses prior to (M2) and after 2012 (M3) showed quite different conclusion in Figure 3. In both time frame, only the USDM had statistically significant the risk ratios of all-cause mortality by 1.046 (95% Cr: 1.021 to 1.071) and 1.057 (95% Cr: 1.022 to 1.093). The remaining drought exposures increased the risk ratios after 2012, with all magnitudes greater than the standard two-stage model (M1). Moreover, the 12-month SPEI and 6-month EDDI prior 2012 (M2) showed protective or null effects with the risk ratios of 0.977 (95% Cr: 0.951 to 1.003) and 0.997 (95% Cr: 0.968 to 1.027). Prior to 2012 (M2), none of the drought exposures had statistically significant risk ratios for cardiovascular mortality. Moreover, drought exposures except USDM reduced the risk ratios. However, there were statistically significant positive associations between cardiovascular mortality and drought exposures (except for the 12-month EDDI) after 2012 (M3). The region had increased risk ratio of 1.076 (USDM, 95% Cr: 1.030 to 1.138), 1.074 (6-month SPEI, 95% Cr: 1.019 to 1.126), 1.081 (12-month SPEI, 95%

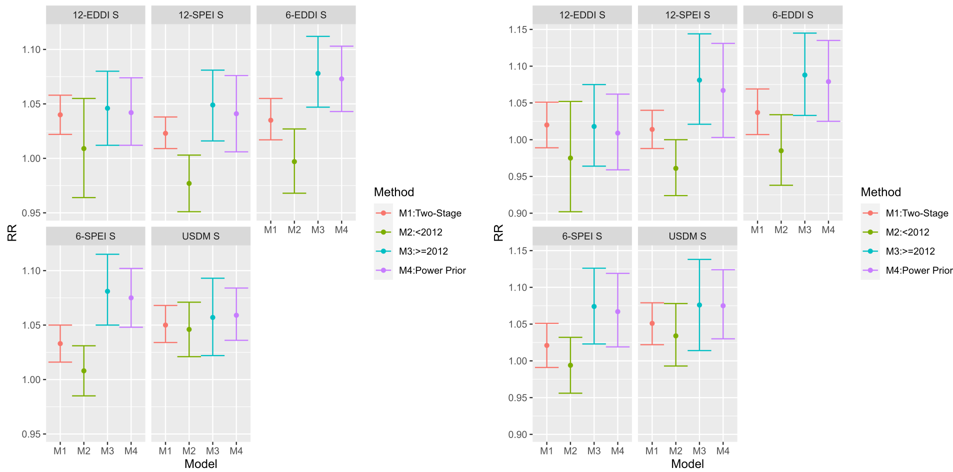

Figure 3: Posterior estimates and its 95% Credible Intervals for the risk ratio associated with different drought exposures by two-stage, separate period, and power prior approach for all-cause (left) and cardiovascular mortality (right). Abbreviations indicate posterior estimate of the overall risk ratio (RR: Risk ratio) and analysis method (M1: standard two-stage model, M2: two-stage model prior to 2012, M3: two-stage model after 2012, M4: two-stage model with the power prior).

Cr: 1.003 to 1.144), and 1.088 (6-month EDDI, 95% Cr: 1.025 to 1.145). The risk ratios previous to 2012 (M2) and after 2012 (M3) had somewhat different magnitudes and directions, as shown in Figure 3, providing a reasonable scientific motivation to propose the power prior approach.

The power prior approach (M4) showed increased statistically significant risk ratios of all-cause mortality associated with all drought exposures. The 6-month SPEI increased the greatest all-cause mortality risk of 1.075 (95% Cr: 1.048 to 1.102) and followed by 1.073 (6-month EDDI, 95% Cr: 1.043 to 1.103), 1.059 (USDM, 95% Cr: 1.036 to 1.084), 1.042 (12-month EDDI, 95% Cr: 1.012 to 1.074), and 1.041 (12-month SPEI, 95% Cr: 1.006 to 1.076). Four drought exposures were identified statistically significant adverse effects in cardiovascular mortality. The risk ratios were 1.075 (95% Cr: 1.030 to 1.124), 1.067 (95% Cr: 1.019 to 1.119), 1.067 (95% Cr: 1.003 to 1.131), and 1.079 (95% Cr: 1.025 to 1.135) by the USDM, 6-month and 12-month SPEI, and 6-month EDDI in order. Statistically significant overall risk ratios from the power prior approach (M4) were greater than the risk ratios by standard time-series model (M1).

5. Discussion

We have examined the overall risk ratios of all-cause and cardiovascular mortalities associated with different severe drought exposures based on multiple drought indices in the Northern Rockies and Plains of the United States between 2000 and 2018. The study has a significant contribution by proposing a new statistical model to integrate heterogeneous time-series data using the two-stage model with the power prior. The proposed approach was motivated by heterogeneous severe drought episodes during study period. Our approach is the first to adequately account for the heterogeneous exposure in health risk assessment and also provides public health implications for risk management associated with drought exposure.

Our main finding is that severe drought exposure has a negative impact on all-cause and cardiovascular mortality in the general population. Results show that all-cause mortality risk ratios were increased by all drought exposures and cardiovascular mortality risk ratio had the same trend, except for the 12-month EDDI (Figure 3). As soils dry out during a drought period, dust and other particles are more likely to circulate in the air, affecting cardiovascular and respiratory diseases (Alpino et al., 2016; Bell et al., 2018; Bellizzi et al., 2020). A geographical feature is of another potential explanation. According to the NCHS 2013 binary rural/urban categorization (Ingram and Franco, 2013), approximately 88.3% of the counties (257 out of 291 counties) in the Northern Rockies and Plains are rural. As agriculture and animal husbandry are the primary sources of income in this region, residents have a greater exposure to outside activity and are expected to be more vulnerable to extreme climate events, such as drought. Another explanation is a high population of the elderly individuals in the area. Pre-existing health concerns, a higher baseline death rate, comorbidities, or poor access medical service are all common among the elderly.

When compared to previous methods, the suggested two-stage model with the power prior approach showed higher risk ratios of all-cause and cardiovascular mortalities (Figure 3). It is of interest in time-series analysis to evaluate the effect of exposure on the outcome across time. The magnitudes and directions of our two separate studies prior to (M2) and after 2012 (M3) varied for overall risk ratios of all-cause and cardiovascular mortalities. As a result, the overall risk ratios in the standard two-stage model (M1) may be underestimated or downgraded. The 6-month and 12-month SPEIs did not have statistically significant overall risk ratios of cardiovascular mortality due to this attenuation. However, in the same situation, the proposed two-stage model (M4) showed higher risk ratios (Figure 3). This finding demonstrates that a statistical model that accommodates distinct time-series patterns captures more stronger associations.

To determine a data-driven similarity between the prior to and after 2012, the discounting parameter a_0 was generated and summarized by Bayesian power prior (M4) in the second stage. The quantity is also interpreted as the amount of information borrowed from the data D_H to estimate the overall risk ratios (See in Figure 1). Based on our findings, the level of borrowing strength or similarity was controlled in our study from 15% to 71%. The value a_0 can be directly calculated using criterion-based method, but several sensitivity analyses should be carried out in the range of the guide values (Ibrahim et al., 2015).

Results from our study showed that the 6-month time-scale drought had higher risk ratios of all-cause and cardiovascular mortality compared to the 12-month drought. This finding is somewhat different from our expectation. We understand that longer-term drought is frequently required to establish prolonged drought and also provides a more complete picture of drought condition. Previous work showed that longer-term (12-month) drought events had more detrimental impacts than the mid-term (6-month) drought (Salvador et al., 2019, 2020b; Lynch et al., 2020; Abadi et al., 2022). However, a recent study found that short-term (3-month) SPEI was associated with cardiovascular mortality in two meteorological stations of the northern Bangladesh (Alam et al., 2022). A short-term (1-month) drought increased the relative risk in circulatory and respiratory mortality in Spain (Salvador et al., 2020c). The combined effect of heatwaves and pollution during drought periods could explain the short-term or mid-term impact of droughts on mortality (Salvador et al., 2020c).

Although this study reported important results, there are also several limitations. First, we considered severe drought exposures based on different drought indices with two timescales in our analysis. We did not provide guidelines or recommendations for drought indicator selection because the number of location-specific risk ratios in the first stage model varied by drought indicator. Further research is needed for recommendation of indicator selection in health risk assessment. Second, we only focused on severe drought events because they had a clear heterogeneous pattern before and after 2012. There were several wave patterns when moderate episodes of drought were evaluated (Figure 2). This is easily applied to the proposed power prior approach with various discounting parameters a_0 (Ibrahim et al., 2015), but additional computing complexity is necessary. Third, throughout the summer, heatwaves occur along with drought, exacerbating the concentrations of air pollution. This may have a higher impact on the mortality risk ratio; but, due to our existing monthly mortality and climatic data, we were unable to evaluate this.

6. Conclusion

Climate change can cause environmental exposures to behave in a different pattern, making health risk assessment associated with these exposures more complex. Our study showed that severe drought had a detrimental impact on all-cause and cardiovascular mortalities in the Northern Rockies and Plains region. Although the primary goal was to develop a novel statistical methodology to assess the impact of the heterogeneous drought exposure pattern on mortality, our findings could be valuable for public health practitioners in delivering early warnings and targeted messaging to populations at risk. We believe that there is a growing need for future research to extensively investigate and understand the health impacts of drought, particularly focusing on demographics such as age group, gender, and race.

Supplementary Materials

The following supporting information can be found at journal website. Section S1: Detailed statistical methodology using the power prior; Table S1: Overall risk ratio estimates and a_0 values of different drought exposures to all-cause mortality; Table S2: Overall risk ratio estimates and a_0 values of different drought exposures to cardiovascular mortality.

Authors Contribution

Y.G.: Conceptualization, Methodology, Analysis, Software, Writing draft. **R.N.**: Analysis, Software. **Y.J.**: Analysis, Software. **A.M.A.**: Conceptualization. **A.R.**: Cleaning and management of weather data. **J.D.B.**: Conceptualization. **J.R.**: Data curation. **R.D.L.**: Data curation. **J.E.B.**: Conceptualization, Methodology. All authors contributed to writing review and editing. Also, all authors have agreed to the submission version of the manuscript.

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Institutional Review Board Statement

This research was approved by the institutional review board at the University of Nebraska Medical Center and was classified as exempt, and does not constitute human subject research as defined at 45CFR46.102.

Data Availability Statement

The mortality data can be requested from the Center for Disease Control and Prevention (CDC) at the following (accessed on 3 January 2023): https://www.cdc.gov/nchs/nvss/nvss-restricted-data.htm. There are detailed instructions on how to access this data, including the project review form and supporting materials that need to be submitted. In order to access the health data, all members must sign a Data Use Agreement (DUA).

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