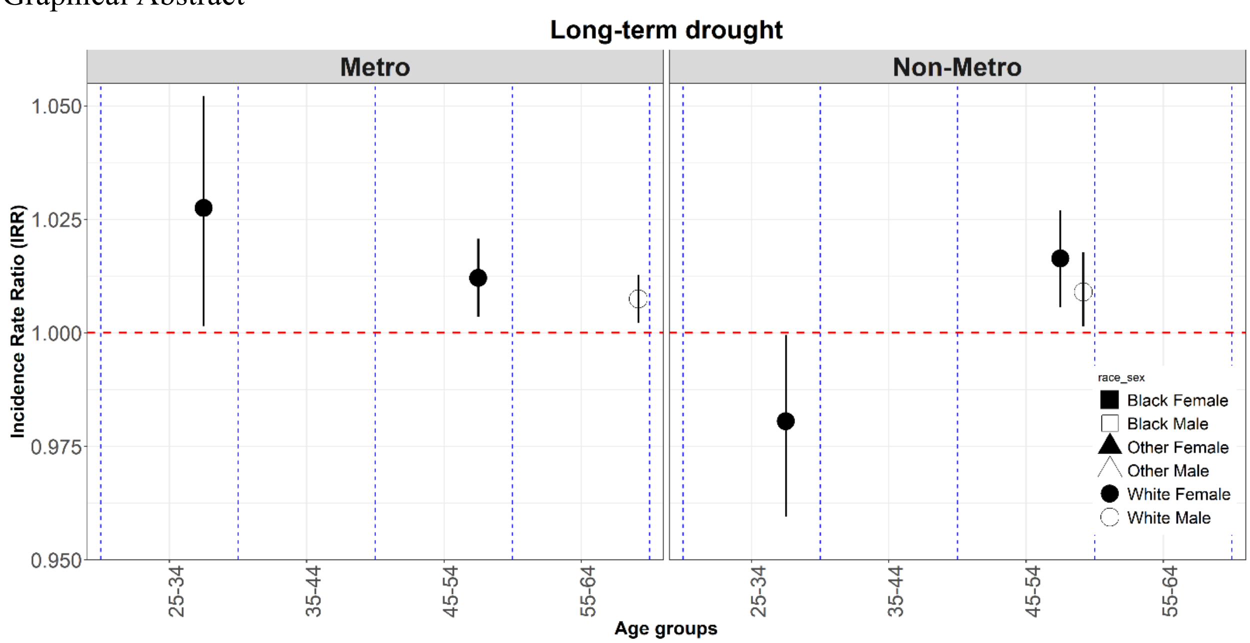
Drought and All-cause Mortality Risk in Nebraska from 1980 to 2014: Time-Series Analyses by Age, Sex, Race, Urbanicity and Temporality of Drought

Highlights

- Studies on drought-related health impacts are sparse.
- There is slightly a negative association between all-cause mortality and drought exposure in the total population, however the effect is statistically null.
- Pathways to drought-related health outcomes are region and demographic group specific.
- White population aged 25-34 and 45-64 were the most population at risk.
- Longer-term droughts are associated with more heightened mortality rates among sub-populations in both metro and non-metro counties, collectively.

Graphical Abstract



Abstract

Background: Climate change will increase drought duration and severity in many regions around the world, including the Central Plains of North America, but studies on drought-related health impacts are still sparse. This study aims to explore the potential impacts of drought on all-cause mortality in Nebraska from 1980 to 2014.
Methods: The Evaporative Demand Drought Index (EDDI) were used to define short-, medium- and long-term drought exposures, respectively. We used a Bayesian zero-inflated censored negative binomial (ZICNB) regression model to estimate the overall impact of drought on annual mortality first in the total population and second in stratified sub-populations based on age, race, sex, and the urbanicity class of the counties.
Results: The main findings indicate that there is a slightly negative association between all-cause mortality and all types of droughts in the total population, though the effect is statistically null. The joint-stratified analysis renders significant results for a few sub-groups. White population

aged 25-34 and 45-64 in metro counties and 45-54 in non-metro counties were the population more at risk in Nebraska. No other positive associations were observed in any other race besides white. Black males aged 20-24 and white females older than 85 showed protective effect against drought mainly in metro counties.

We also found that more sub-populations had higher rates of mortality with longer-term droughts compared to shorter-term droughts (12-month vs 1- or 6-month timescales), in both metro and non-metro counties, collectively.

Conclusion: Our results suggest that middle aged white population in Nebraska are more vulnerable to the negative impacts of drought. Moreover, women aged 45-54 were more affected than men in non-metro counties. With a projected increase in the frequency and severity of drought due to climate change, understanding these relationships between drought and human health will better inform drought mitigation planning to reduce potential impacts.

Keywords: climate change; health disparities; urbanicity; Evaporative Demand Drought Index (EDDI); all-cause mortality

1. Introduction

Drought is a complex phenomenon that results from an extended period of hydrological imbalance between moisture supply (e.g., precipitation) and demand, relative to long-term average conditions (Hobbins et al., 2016). NOAA's Billion Dollar Disasters report lists drought as the third costliest extreme event in the United States after tropical cyclones and severe storms, with an aggregated economic loss of $285.4 billion from 1980 to 2021 (NCEI, 2022). In terms of loss of human lives, drought is ranked second in the United States after tropical cyclones, with an average number of deaths of 95 per year. While there is extensive research on the health effects of extreme weather events such as hurricanes, wildfires, and floods, research on drought-related health outcomes is still nascent and limited. This is mainly due to the nature of the event and our lack of understanding of the threat that drought poses to human health (Wilhite & Glantz, 1985; Mishra & Singh, 2010).

Drought has direct and indirect health consequences that are mainly associated with changes in water quality and quantity during and after the event. However, unlike other natural disasters, these health complications are not as obvious and immediate. This is mainly due to the slow, or in some cases more rapid evolving, nature of drought, the fact that there are no clear start and ending dates for droughts, the various time spans and severity and co-occurrence with heat waves, wildfire, and air pollution (Bell et al., 2016; Weilnhammer et al., 2021). Monitoring of drought is defined by short- to long-term physical changes to the environment and impacts on supply and demand in the socioeconomic systems and/or water availability (Wilhite and Glantz, 1985; Mishra and Singh, 2010, Crausbay et al., 2017). In drought monitoring, meteorological drought reflects the deficit in moisture supply (i.e., precipitation) that may be best represented by shorter timescales of 1-3 months. Agricultural drought is reflected by soil moisture deficit through evapotranspiration and may be best represented by 3–6-month timescales (Ji & Peters, 2003). Finally, hydrological drought is a response to moisture deficit through runoff along with surface and groundwater depletion and may be best represented by timescales longer than 12 months (Gibs & Mahr, 1967; Wilhite & Glantz, 1985). The impacts of these various timescales on the environment adds to the complexity of the assessment of the health impacts of the drought.

The existing epidemiological studies suggest a variety of direct and indirect health outcomes associated with drought (Sugg et al., 2020; Lynch et al., 2020; Ebi et al., 2021) including access to fresh water, sanitation and hygiene needs (Bellizzi et al., 2020; UNDRR, 2021), food insecurity and malnutrition (Watts et al., 2017), cardiovascular, respiratory, heat-related issues (Stanke et al., 2013; Berman et al., 2017; Bell et al., 2018), mental health disorders (Stanke et al., 2013; Vins et al., 2015), conflict and violence in resource-limited areas (Bell et al., 2018), waterborne and vector-borne diseases (Hayes, 2002; Yusa et al., 2015; Bell et al., 2018) and morbidity and mortality (Ebi and Brown, 2016; Salvador et al., 2020b, ; CRED, 2019; Lynch et al., 2020). Several studies have investigated the potential relationship between drought and mortality across the world. Berman et al. (2017) showed that worsening drought conditions in the western U.S. are associated with increased rate of mortality, especially in regions less frequently experiencing drought. Lynch et al. (2020) did not find a significant association between short-term drought severity and all-cause mortality in the overall U.S. population but found positive associations for age groups between 25-64 for mostly white population subgroups. Salvador et al. (2020b) studied the impact of short-term and short to medium-term drought on daily specific cause mortality in Spain and found that among the different timescales, longer-term drought increased the mortality rate due to respiratory issues. They also found that the greatest drought-related risk of daily mortality was associated with natural, circulatory, and respiratory causes that in regions with higher percentage of populations over 65 years of age. Salvador et al. (2019) found a significant association between drought periods and daily mortality in Galicia, Spain, with the effect being greater in the inland provinces than in coastal regions. They also found that in short term, respiratory causes of mortality were the most strongly positively associated cause of death. In another study, Salvador et al. (2021) showed association between drought and all-cause mortality in Lisbon, Portugal, with the risk of mortality highest for the oldest population and men being more affected than women. They also concluded that the mortality was largely explained by pollution and heat often linked with short-term droughts. In another study in urban areas of Brazil, Salvador et al. (2022) found an overall positive association between drought exposure and non-external circulatory and respiratory mortalities. They also concluded that female, children, and elderly population were the most affected groups. Studies also have shown an association between drought and mental health outcomes among farmers in rural areas in different parts of the world (Vins et al., 2015; Herold et al., 2018; Parida et al., 2018; Berman et al., 2021). For example, a study in the state of New South Wales, Australia showed an increase in the relative risk of suicide among rural males aged 30-49 when the Hutchinson Drought Index increases from the 1st quartile to the 3rd quartile, while the relative risk decreased in women aged >30 (Hanigan et al., 2012).

Different studies reveal that not all subgroups within population are equally affected by the adverse effects of drought (Stanke et al., 2013; UNDRR, 2021). Understanding the geographic and demographic factors and identifying the most affected sub-populations enable public health officials and policy makers to design targeted mitigation strategies to reduce the health burden of the drought (Vogt et al., 2018; UNDRR, 2021). Most commonly used factors in climate change-related mortalities include, but not limited to, demographic factors such as age, sex and race and geographic factors such as urban vs. rural. Most of these factors have been studied in drought-related health research. Multiple studies have shown that children and the elderly population are more vulnerable to the impacts of drought (Stanke et al., 2013; Salvador et al., 2021; Lynch et al., 2020; Salvador et al., 2022). Drought also affect men and women differently (Salvador et al., 2020b). Some studies have shown that women are more vulnerable during drought due to different coping mechanisms in different cultures (Myeni & Wentink, 2021; Algur et al., 2021), while other studies such as Salvador et al. (2021) concluded that men being more affected that women. Climate change-related health studies present significant evidence that often in the United States, race is an important predictor for environmental inequities (Wikstrom at al., 2018; McDermott-Levy et al. 2021). This also applies to the drought-related health studies (Lynch et al., 2020; Matlock, 2019). For example, MacDonald Gibson et al. (2014) in a study in North Carolina towns concluded that increases in the African American population proportion within a census block correlated with an increase in the odds of exclusion from municipal water service. On the role of urbanicity, studies also have shown that rural and farming communities are more vulnerable to negative impacts of drought, specifically in the context of mental health (Vins et al., 2015; Berman et al., 2021). Though, the impact is not limited to mental health. Multiple factors affect rural communities being less resilient to climate disasters such as drought including occupation, earnings, lifestyle, older population, remoteness, and lack of access to proper healthcare (Lal et al., 2011). Drought and water scarcity also can affect urban residents' physical and mental health through different pathways such as heat-related illnesses, air pollution, less activities and worsening mental health due to diminished green spaces (Abadi et al., 2020). However, there is still a gap in the literature on the differences between health outcomes in rural vs urban settings.

The Central Plains region of the United States is susceptible to various types of drought that can occur with high spatial and temporal variability (Zambreski et al., 2018). Recent studies are providing strong evidence that climate change will increase drought risk and severity in many regions of the world (Wehner et al., 2017; Hoegh-Guldberg et al., 2018). The Central Plains in North America is among the regions projected to experience widespread decrease in surface soil moisture (Oglesby et al., 2015; Cook et al., 2015; Wilhite and Morrow, 2016). As agriculture is a primary source of income in this region, populations are more vulnerable to extreme climate variability, such as drought. Drought is the costliest natural hazards in Nebraska with estimated losses of $10-20 billion statewide from 1980 to 2021 (NCEI, 2022). Almost half of all the total costs of extreme events in Nebraska from 1980 to 2021 are associated with drought, with the highest losses occurring with droughts in the 2010s (NCEI, 2022). A few studies focused on Nebraska have found health outcomes associated with drought. Smith et al. (2020) found that high temperatures and a dry year preceded by wet years were strongly associated with the increased number of West Nile Virus cases. Figgs (2020) found that Emergency Department visits in Douglas County due to chronic bronchitis diagnosis were higher among female subjects during a 2012 heatwave and drought relative to the same period in 2011. In another study, Figgs (2019) showed that the Asthma ED diagnosis risk for African American males aged <19 in Douglas County was elevated during the 2012 drought and heatwave period compared to 2011. High levels of cyanobacteria in two lakes in Nebraska raised health issues in 2004, with later assessments showing that drought conditions partially contributed to the lower nitrogen-to-phosphorus ratios that led to increased numbers of cyanobacterial complaints (Walker et al., 2008).

In this study, we aim to use Bayesian models to identify the association between various types of drought and annual all-cause mortality in Nebraska. Vulnerability will be evaluated by age, race, sex, and urbanicity. Our work supports the hypothesis that drought is associated with higher rate in mortality in certain population groups. The findings of this study enable us to identify populations vulnerable to the impacts of drought and to inform public health authorities to implement more effective strategies to mitigate negative impacts. Further, identifying the high-risk population sub-groups will also enable us to study the specific causes in future studies.

2. Material and Methods

2.1. Mortality Data

Mortality and population data were extracted from the Mortality and Population Data System (MPDS) from 1980-2014 (http://cobe.biostat.pitt.edu/ocmap.html) (Marsh et al.,1998). Data include the annual death counts for all causes on a standard 63-cause list in 93 counties in Nebraska (NE). The data are also further stratified by two sex groups of "Male" and "Female", three race groups of "White," "Black," and "Others", and 13 age groups of 1) "<1", 2) "1-4", 3) "5-9", 4) "10-14", 5) "15-19", 6) "20-24", 7) "25-34", 8) "35-44", 9) "45-54", 10) "55-64", 11) "65-74", 12) "75-84", and 13) ">85". All death counts falling between [1-9] are suppressed due to the National Center for Health Statistics (NCHS) privacy policy. To address this, we use interval censoring approach to account for the censored death counts rather than mid-point imputation (Bartell & Lewandowski, 2011).

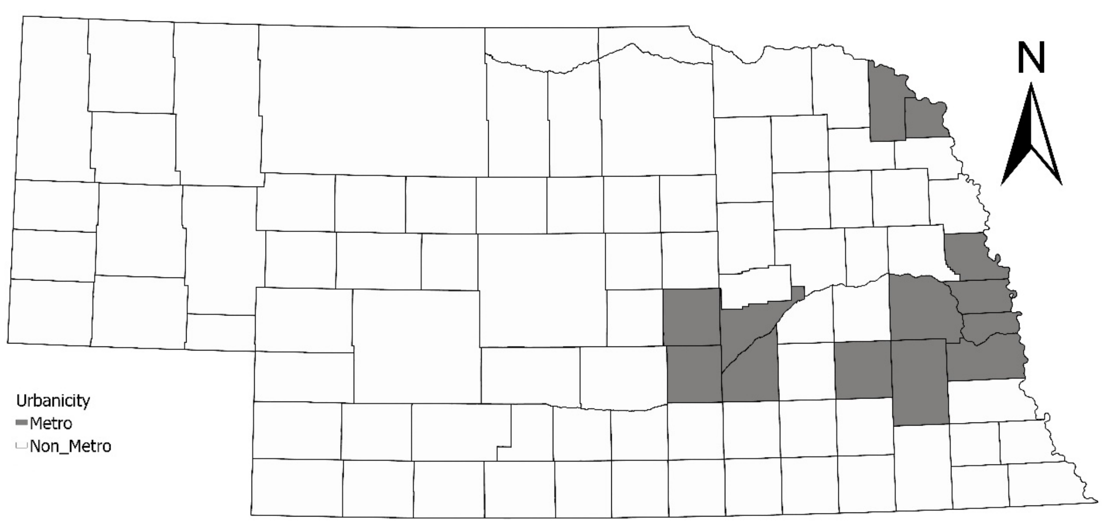


Figure 1. Urban-Rural classification schemes in Nebraska based on 2013 NCHS classification. According to the 2013 NCHS classification schemes, 13 of the 93 counties in Nebraska fall into the union of all metro categories (Cass, Dakota, Dixon, Douglas, Hall, Hamilton, Howard, Lancaster, Merrick, Sarpy, Saunders, Seward, and Washington). Four counties of Hall, Hamilton, Howard, and Merrick are categorized as non-metro in the 2006 NCHS classification but are classified as metro in the newer Urban-Rural Classification scheme. The rest are classified as non-metro.

Urban-Rural classification differences have been recognized and applied to many health studies. For this study, we used the binary classification of Metro (1) vs Non-metro (0) based on the 2006 and 2013 NCHS Urban-Rural classification schemes for the counties in Nebraska (Ingram and Franco, 2013). The schemes categorize the US counties and county equivalents to six urbanicity levels, of which four are metropolitan, including "Large central metro," "Large fringe metro," "Medium metro," and "Small metro," while two are non-metropolitan, including

"Micropolitan" and "Noncore." The 2006 scheme was used for the period 1980-2012 and the 2013 NCHS scheme was used for years 2013 and 2014. In Nebraska, 13 of 93 counties are categorized as metro, covering only 9% of the state by area and containing 65% of the total population (Fig. 1).

2.2. Drought Exposure

Drought indices typically quantify and monitor drought status using single, multiple, or a composite set of hydrometeorological indicators. The Evaporative Demand Drought Index (EDDI) measures the signal of drought through the response of atmospheric evaporative demand (E0) to surface drying anomalies (Hobbins et al., 2016; McEvoy et al., 2016). E0 may be considered a measure of the "thirst of the atmosphere"; its estimation is independent of precipitation as it is driven solely by temperature, humidity, wind speed, and incoming solar radiation. EDDI can be calculated at different timescales to represent different drying dynamics, from the weather scale (e.g., 1 week) to the annual scale (1 year). EDDI values are obtained by deriving empirical probabilities of aggregated E0 depths relative to their climatologic means across a user-specific time period (i.e., the timescale) and normalizing these probabilities (Hobbins et al., 2016). Positive EDDI values indicate conditions drier than normal and negative values indicate wet anomalies. In this study, we opted for 1-, 6-, and 12-month EDDI timescales to represent different temporal aggregations and drought durations, respectively. EDDI values for different timescales were downloaded from NOAA's Physical Sciences Laboratory (https://downloads.psl.noaa.gov/Projects/EDDI/CONUS_archive/data/).

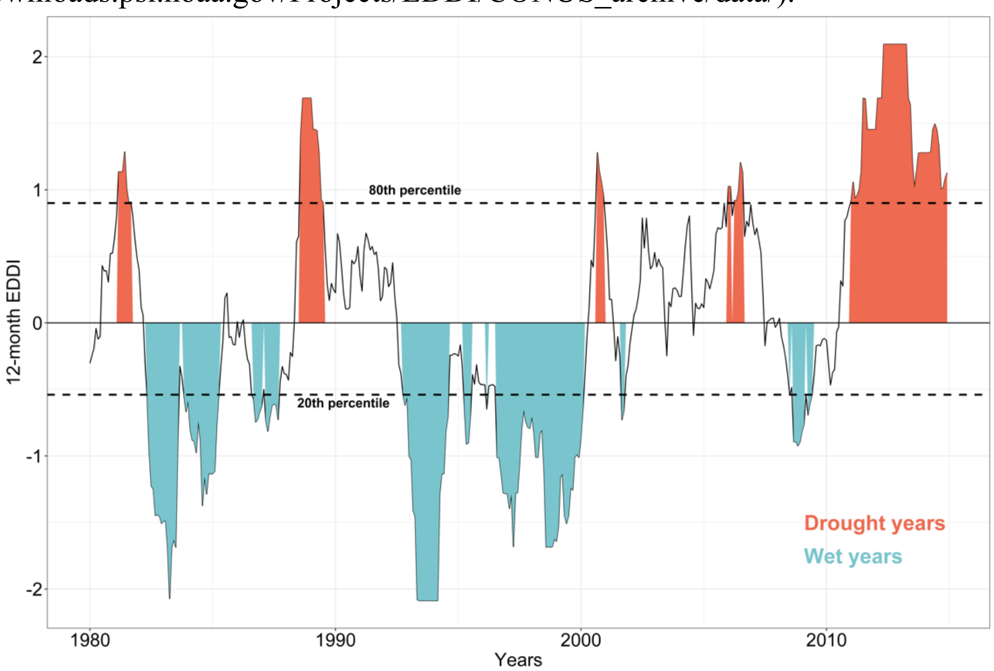


Figure 2. Drought and wet events were defined by EDDI values above (below) the 80^{th} (20^{th}) percentile for two or more consecutive months. This figure shows the drought (denoted in red) and wet (denoted in blue) events based on the 12-month EDDI for Douglas County, Nebraska.

In each county in Nebraska and for each EDDI timescale, we defined drought events if the EDDI value of the month was above the 80^{th} percentile at least for two consecutive months. In an opposite manner, a wet event was defined if the monthly EDDI values were below 20^{th}

percentile for at least two consecutive months in each EDDI timescale monthly time series. Figure 2 shows an example of how drought and wet events were defined for 12-month EDDI timeseries in Douglas County, NE. Further, following the approach presented in Lynch et al. (2020), the months in drought and wet events were assigned monthly indicators of 1 and -1, respectively. The months that were not either in a drought or wet event were assigned a monthly indicator of 0. To develop the annual index for drought exposure, we multiplied the monthly indicators by their corresponding EDDI values and summed the resulting numbers over each year. To only focus on the drought exposure in this study, we also removed the wet years from our analysis. Wet year is defined if the annual drought index is negative. This approach was repeated for each of our 1-, 6 and 12-month timescale time series.

2.3.Statistical Analysis

We used a Bayesian zero-inflated censored negative binomial (ZICNB) regression model to identify an association between all-cause mortality count and annual drought severity in Nebraska. To estimate the overall impact of drought on the total population, we first considered a basic model with the drought score as the main exposure, and controlled for age, race, sex, urbanicity level and the temporal variability. To count for the temporal trend, we used a standardized year variable. We did not conduct a county-specific model due to the low number of cases in each county and to avoid convergence issues. Further, we ran joint stratification analyses by age, race, sex, and urbanicity to identify vulnerable population sub-groups to drought exposure by individual joint stratum. To address censoring mortality counts (ranging from 1 to 9), we considered interval-censored approach. Following Lynch et al. (2020), the conditional likelihood is used for the number of deaths with censored interval 1 to 9, which is given as:

$$P(1 \leq y_{it} \leq 9|x_{it}) = P(y_{it} = 1|x_{it}) + \cdots + P(y_{it} = 9|x_{it})$$

where y_{it} is the number of deaths at county i and year t.

We also included the natural logarithm of the population as an offset term in the model. The proposed model is given by

$$log\left(\frac{\pi_{it}}{1-\pi_{it}}\right) = \boldsymbol{x}'_{it1}\boldsymbol{\beta}_1 \,, \qquad log(\mu_{it}) = \boldsymbol{x}'_{it2}\boldsymbol{\beta}_2 + \xi_i$$

where $\xi_i \sim N(0, \sigma^2)$, π_{it} and μ_{it} are the probabilities of extra zeros and the expected negative binomial count, respectively, $\boldsymbol{x}_{it1}$ and $\boldsymbol{x}_{it2}$ are vectors of covariates including exposure, and $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are the corresponding vectors of regression coefficients. The proposed Bayesian ZICNB regression model is attractive by (i) accounting for the censored death count; (ii) modeling the large proportions of zero counts; and (iii) quantifying heterogeneity across counties through random intercept.

To complete a Bayesian model specification, we specify the priors on the model parameters. An inverse-gamma prior and gamma prior are placed on the variance as $\sigma^2 \sim IG(0.01, 0.01)$ and dispersion parameter as $Gamma(3,2)$. For regression coefficients on $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$, we use weakly informative prior distributions $N(0,100)$. Posterior inference is carried through the Markov chain Monte Carlo (MCMC) sampling algorithm (Gelfand and Smith, 1989). The statistical significance for the parameter was determined if the corresponding 95% Highest Posterior Density (HPD) interval of the parameter does not include the value of 0. The exposure-related regression coefficient is the difference between the logs of expected counts implying a one unit change in the exposure variable (annual drought index). As the difference of two logs is equal to the log of their quotient, the parameter estimate can also be interpreted as the log of the ratio of expected counts. In addition, what we referred to as a count is technically a rate as it is the mortality number of deaths per year. So, the exponential of the exposure-related regression coefficient can be interpreted as Incidence Rate Ratio (IRR). The estimated IRR should be interpreted as follows: the posterior estimate of IRR value greater than 1 indicates increased mortality rate with one unit increase in the annual drought exposure; an IRR value less than 1 indicates decreased mortality rate with one unit increase in the annual drought exposure; and finally, an IRR value equal to 1 indicates no impact of the annual drought exposure on the mortality rate. In other words, as the annual drought exposure (EDDI) is measured as a continuous scale, we use a standard interpretation way as: (1) as the annual drought increases one unit, say, β=0.1 the mean IRR increases 10.5% ($e^{0.1}$=1.105). (2) If the annual drought decreases by -0.1 (β=-0.1), the mean IRR decreases by 9.5% ($e^{-0.1}$=0.905). We use 20,000 MCMC samples, which were taken from every 10th iteration, after a burn-in of 2,000 iterations to compute all posterior estimates. All analyses were conducted by Statistical Analysis System (SAS) version 9.4 and Metropolis-Hasting sampler was used for sampling algorithm in PROC MCMC procedure. MCMC convergence were checked using trace plots, autocorrelation plots, and the diagnostic procedures discussed in Chen et al. (2000). The HPD intervals are computed via the Monte Carlo method developed by Chen and Shao (1999), which is a default option in PROC MCMC.

3. Results

3.1. Descriptive analysis

The descriptive statistics of all cause-mortality in Nebraska from 1980 to 2014 are presented in Table 1. The statistics are categorized based on 13 age groups, three race categories, and two sex categories. Almost 19% (18.7%) of the total data are suppressed with values falling between 1 and 9. Due to the censored values in the dataset, we could not calculate the total mortality in the study period. The mortality is higher in the white population in general as 88% of Nebraska's population are listed as white (U.S. Census Bureau, 2016). In almost all age groups and races, the mortality among men is higher than that of women. Overall, mean mortality increases with age in all population strata. As observed in all population strata across time, the standard deviation of total deaths exceeds the mean, indicating overdispersion in the mortality distribution. To account for overdispersion, we used the negative binomial model rather than Poisson model. The two rightmost columns of Table 1 also show the percentage of zeros in each population stratum; this is highest for races other than white, which further justifies our choice of applying zero-inflated models.

Table 1. Descriptive statistics corresponding to annual all-cause mortality counts in Nebraska from 1980 to 2014. Mortality is categorized by thirteen age groups, three race categories, and two sex categories. The rightmost two columns show the percentage of zero deaths in each sub-population. Percentages above 90 are in bold. Due to the suppression issues, we could not obtain max value for some strata in the table ("-"). Standard deviation is abbreviated as SD. N indicates the sample size in each population sub-group.

Age group	Race	Summary statistics for death counts										Percentage of zero	
		Male					Female						
		N	mean	SD	min	max	N	mean	SD	min	max	Male	Female
<1	White	3244	1.66	3.29	0	35	3251	1.39	2.72	0	23	61.31	67.88
1-4		3255	0.56	1.59	0	10	3255	0.45	1.43	0	-	85.15	88.15
5-9		3255	0.42	1.39	0	-	3255	0.35	1.27	0	-	88.26	**92.27**
10-14		3255	0.56	1.58	0	-	3255	0.40	1.36	0	-	84.72	**90.41**
15-19		3255	1.50	2.46	0	17	3255	0.85	1.90	0	10	64.84	80.26
20-24		3255	1.74	2.88	0	24	3255	0.74	1.78	0	10	64.01	83.02
25-34		3255	2.49	4.53	0	52	3255	1.40	2.72	0	22	55.71	73.44
35-44		3255	3.47	6.69	0	78	3255	2.51	4.23	0	43	45.48	58.22
45-54		3255	6.00	13.64	0	146	3255	4.25	8.29	0	86	26.13	38.21
55-64		3255	9.75	24.64	0	294	3255	6.83	15.67	0	171	12.08	20.48
65-74		3255	15.19	37.55	0	414	3255	11.24	27.92	0	325	6.02	9.77
75-84		3255	22.28	48.98	0	488	3255	21.05	51.25	0	488	4.19	6.15
85+		3254	18.54	37.55	0	450	3249	35.07	74.95	0	774	6.59	5.42
<1	Black	864	0.46	1.84	0	20	833	0.46	1.85	0	17	**97.30**	**97.51**
1-4		1496	0.15	0.84	0	-	1490	0.07	0.58	0	-	**98.56**	**98.99**
5-9		1546	0.07	0.60	0	-	1552	0.06	0.55	0	-	**99.11**	**99.36**
10-14		1560	0.08	0.64	0	-	1493	0.07	0.61	0	-	**99.08**	**99.29**
15-19		1506	0.17	0.92	0	-	1390	0.09	0.65	0	-	**98.35**	**98.95**
20-24		1311	0.24	1.13	0	10	1190	0.17	0.90	0	-	**98.19**	**98.72**
25-34		1550	0.42	1.85	0	17	1254	0.18	0.94	0	-	**96.96**	**98.15**
35-44		1427	0.49	2.34	0	22	1185	0.32	1.54	0	17	**97.37**	**97.83**
45-54		1264	0.89	4.37	0	42	1081	0.70	3.44	0	28	**96.73**	**97.41**
55-64		978	1.51	7.05	0	58	903	1.16	5.49	0	56	**96.23**	**97.00**
65-74		650	2.05	8.14	0	51	643	1.84	7.02	0	44	**95.81**	**96.48**
75-84		516	2.45	9.05	0	56	580	2.50	9.54	0	59	**96.20**	**96.41**
85+		239	2.41	6.11	0	25	471	2.78	10.18	0	62	**97.28**	**96.45**
<1	Other	1213	0.35	1.27	0	-	1267	0.25	1.08	0	-	**96.89**	**97.28**
1-4		2015	0.04	0.42	0	-	2052	0.04	0.44	0	-	**99.34**	**99.43**
5-9		2241	0.02	0.30	0	-	2198	0.02	0.34	0	-	**99.57**	**99.73**
10-14		2181	0.03	0.37	0	-	2291	0.00	0.00	0	-	**99.54**	**99.79**
15-19		2305	0.07	0.61	0	-	2251	0.08	0.61	0	-	**98.76**	**99.27**
20-24		1873	0.15	0.86	0	-	1986	0.05	0.50	0	-	**97.74**	**99.11**
25-34		2171	0.22	1.03	0	-	2368	0.14	0.83	0	-	**96.25**	**97.39**
35-44		2121	0.35	1.28	0	-	2340	0.22	1.03	0	-	**95.72**	**96.55**
45-54		1939	0.44	1.42	0	-	2274	0.35	1.28	0	-	**93.91**	**95.06**
55-64		1730	0.55	1.56	0	-	1962	0.42	1.43	0	11	**93.73**	**94.01**
65-74		1346	0.62	1.65	0	-	1562	0.53	1.54	0	-	**93.30**	**94.23**
75-84		902	0.55	1.56	0	-	1158	0.66	1.69	0	-	**94.35**	**93.94**
85+		463	0.45	1.44	0	-	608	0.61	1.63	0	-	**96.57**	**95.65**

3.2. Overall impacts of drought

Given that the majority of data presented in Table 1—specifically races other than white—had zeros in mortality, we applied a zero-inflated censored negative binomial with random intercept model to capture the heterogeneity across counties. To estimate the overall impact of drought on the total population, we first considered a basic model with only drought index as the main exposure and adjusted for age, race, sex, urbanicity level, and the temporal trend in our model.

Table 2 displays a summary of the posterior estimates including posterior mean and its 95% HPD interval, standard deviation (SD), and the IRRs and their 95% HPD interval. We observed that all drought types are negatively associated with all-cause mortality in the total population and the IRR values vary between 0.99900 [0.99700, 1.00100] and 0.99993 [0.99686, 1.00295] (Table 2). However, this association is not statistically significant as the 95% HPD interval does include the value of 0. Age, race, and sex are all significantly associated with higher rate of all-cause mortality. Urbanicity was not significant in the basic model, but we kept it in the model.

Table 2. Basic models' results for the total population. The table includes the drought timescale, posterior mean and the corresponding highest posterior density (HPD) intervals, standard deviation (SD), Incidence rate ratio (IRR) values and corresponding intervals of all-cause mortality for different covariates in the model including drought (main exposure), age, race, sex, year, and urbanicity level for three timescales of drought based on different accumulation periods.

Drought Timescale	Parameter	Posterior Mean (95% HPD)	SD	IRR (95% HPD)
1-month	**Drought**	-0.00007 (-0.00314, 0.00295)	0.0015	0.99993 (0.99686, 1.00295)
	Age	0.61220 (0.60600, 0.61860)	0.0032	1.84448 (1.83308, 1.85633)
	sex (Male vs Female)	0.33850 (0.31580, 0.36210)	0.0121	1.40284 (1.37136, 1.43634)
	race (White vs Other)	0.60600 (0.53410, 0.68070)	0.0375	1.83308 (1.70591, 1.97526)
	race (Black vs Other)	0.42070 (0.28920, 0.56720)	0.0731	1.52303 (1.33536, 1.76332)
	Year	-0.08910 (-0.10110, -0.07660)	0.0061	0.91475 (0.90384, 0.92626)
	Urbanization level (metro vs non-metro)	0.03580 (-0.06150, 0.14090)	0.0511	1.03645 (0.94035, 1.15131)
6-month	**Drought**	-0.00064 (-0.00254, 0.00136)	0.0010	0.99936 (0.99746, 1.00136)
	Age	0.61260 (0.60620, 0.61900)	0.0032	1.84522 (1.83345, 1.85707)
	sex (Male vs Female)	0.34040 (0.31790, 0.36330)	0.0116	1.40551 (1.37424, 1.43807)
	race (White vs Other)	0.59210 (0.52420, 0.67350)	0.0377	1.80778 (1.68911, 1.96109)
	race (Black vs Other)	0.49380 (0.35780, 0.61440)	0.0660	1.63853 (1.43018, 1.84855)
	Year	-0.08700 (-0.09870, -0.07450)	0.0063	0.91668 (0.90601, 0.92821)
	Urbanization level (metro vs non-metro)	0.01870 (-0.08190, 0.10720)	0.0479	1.01888 (0.92136, 1.11316)
12-month	**Drought**	-0.00100 (-0.00300, 0.00100)	0.0010	0.99900 (0.99700, 1.00100)
	Age	0.61300 (0.60700, 0.61900)	0.0030	1.84596 (1.83492, 1.85707)
	sex (Male vs Female)	0.34000 (0.31800, 0.36400)	0.0120	1.40495 (1.37438, 1.43907)
	race (White vs Other)	0.59200 (0.52000, 0.66200)	0.0370	1.80760 (1.68203, 1.93867)
	race (Black vs Other)	0.51300 (0.41400, 0.60400)	0.0500	1.67029 (1.51286, 1.82942)
	Year	-0.08600 (-0.09800, -0.07400)	0.0060	0.91759 (0.90665, 0.92867)
	Urbanization level (metro vs non-metro)	0.02400 (-0.06100 0.10600)	0.0440	1.02429 (0.94082, 1.11182)

3.3. Drought impacts on all-cause mortality in Age-Race-Sex-Urbanicity joint-stratified Strata

To quantify the effects of drought on sub-population levels, we ran separate models for each age-race-sex stratum with two urbanicity levels of metro vs non-metro (Total of 156 models for all the combinations of 13 age groups, 3 race categories, 2 sex categories and 2 urbanicity levels of metro vs non-metro). Since drought affect different population sub-groups differently, we hypothesize that this stratification will render more meaningful results. Figure 3 summarizes the posterior IRR estimates and the 95% HPD intervals for marginal drought impact on mortality for the significant sub-groups for short (top panel), short to medium (middle panel), and long-term droughts (bottom panel), respectively. More information on the effect estimates on all population sub-groups including the non-significant results can be found in supplementary tables 1-3. The emphasis here has been on the effect of the drought exposure in non-zero mortality counts. As the IRR is the exponential of the posterior mean, the negative and positive associations are marked by values less than 1 and larger than 1, respectively.

Positive associations were mostly observed in both women and men in the white population by different drought types both in metro 1.054[1.009,1.097], 1.007[1.001,1.013], 1.007[1.002,1.013], 1.027[1.001,1.052], 1.012[1.004,1.021], and non-metro counties 1.016[1.001,1.031], 1.013[1.002,1.023], 1.009[1.001,1.018], 1.016[1.006,1.027].

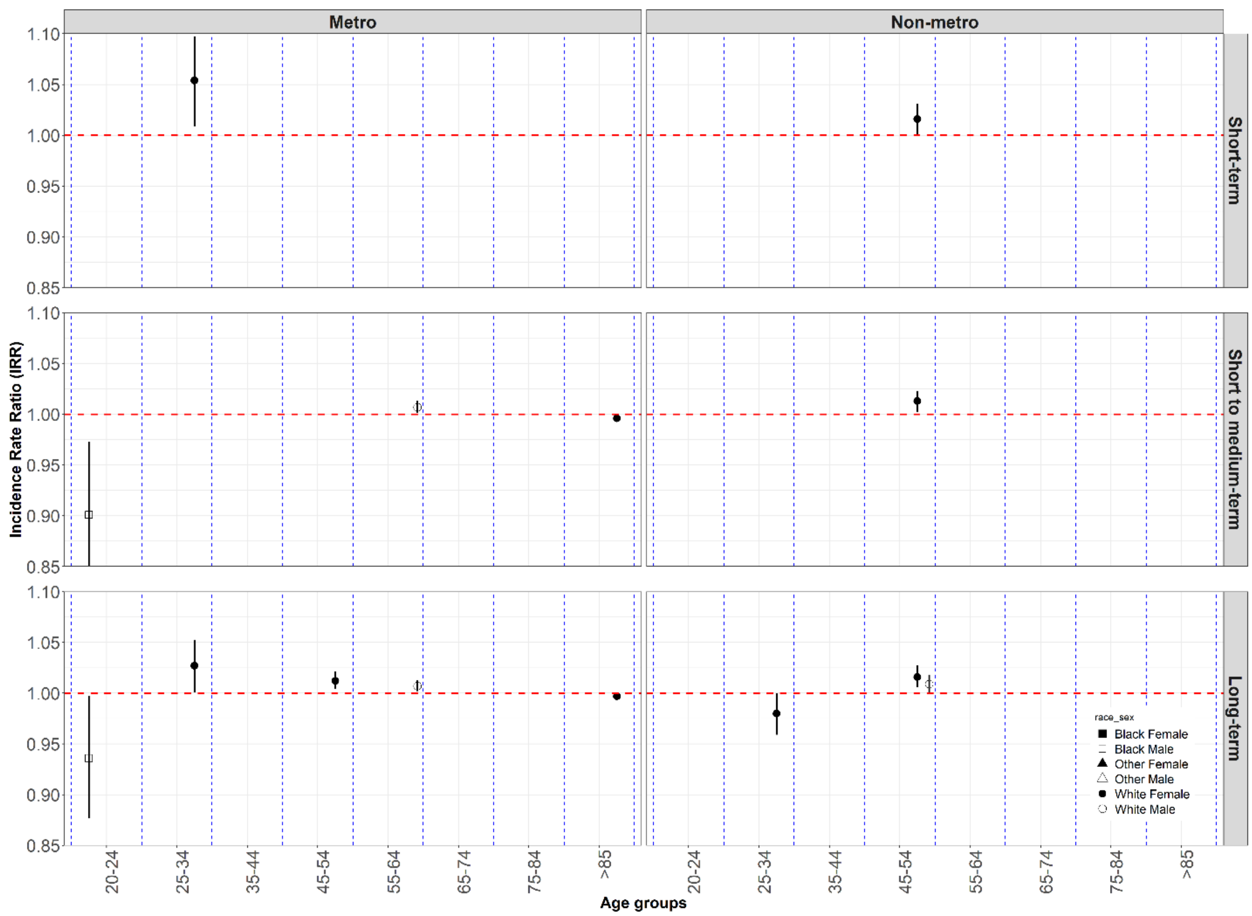


Figure 3. Incidence Rate ratios and their corresponding highest posterior density (HPD) intervals of the effect of short to long-term droughts on all-cause mortality in age-race-sex population strata in metro and non-metro counties in Nebraska from 1980 to 2014. Only the significant results have been shown here and the non-significant sub-groups have been removed from the plots. IRR greater than 1 indicates an increase in mortality with increase in the drought exposure.

A negative association was observed for young black men (20-24) for longer droughts in metro counties with IRR values of 0.901 [0.832,0.973] and 0.936 [0.877,0.997] for short to medium and long-term droughts, respectively. The results also show that only the adult population (>19) is impacted by drought in the state. Among white population, mortality rate increased significantly in white males and females aged 45-54, both in metro and non-metro counties, and 55-64, only in metro counties, ranging from 1.007 [1.002,1.013] to 1.054 [1.009,1.097] during all short-term to long-term droughts (except during short-term droughts in metro counties). White females aged 45-54 are vulnerable to all types of drought (especially in non-metro counties), whereas white males aged 55-64 are vulnerable to longer-term drought (especially in metro counties). Drought also influenced positively on mortality rates in young white women aged 25-34, 1.054[1.009,1.097] for short- and 1.027[1.001,1.052] for long-term droughts mostly in metro counties. However, a negative association was observed in the eldest women (85+) for longer-term drought, in metro counties with IRRs 0.996[0.993,0.999] and 0.997[0.994,0. 999] for short to medium and long-term droughts. Respectively. Comparing metro vs non-metro results, we also found out that only mortality in white females aged 25-34 and 45-54 and males aged 55-64 had statistically positive association with drought exposure, while in non-metro, mortalities only in white male and females aged 45-54 were positively associated with drought exposure. Also, white females aged 45-54 was the only population sub-group that showed statistically significant positive association between all-cause mortality and long-term drought both in metro and non-metro, though the effect estimate was higher in non-metro (1.016[1.006,1.027]) vs metro stratification (1.012[1.004,1.021])). Finally, according to time scales, short-term drought increased the risk of all-cause mortality only in females. The results show that more sub-population strata are significantly vulnerable to longer-term drought (12-months) rather than shorter droughts (e.g., 1-month timescale).

4. Discussion

This epidemiological study is the first study to evaluate the association between drought with various timescales and mortality in population sub-groups in Nebraska from 1980-2014. We used a Bayesian modeling approach to investigate the impacts of drought on all-cause mortality in total population controlling for age, sex, race, urban-rural classification, and temporal variability. We also conduct a joint stratified assessment based on age-sex-race-urbanicity to determine the structure of the population mostly at risk. To assess drought exposure, we used the Evaporative Demand Drought Index (EDDI) in three timescales, with 1-, 6- and 12-month representing short-, short-medium and long-term droughts, respectively. EDDI is a relatively new drought index that is able to capture the early signals of water stress that has demonstrated skill in early warning of both rapidly evolving (“flash”) droughts and sustained droughts. Unlike other drought indices, where negative values indicate drought, positive values in EDDI are the indicator of drought, therefore a positive coefficient means that increase in mortality rate is associated with increase in the drought severity. Overall, the main findings suggested a null result for association between drought and all-cause mortality in the total population in Nebraska. These effects were uneven for the different sub-groups in the population.

Controlling for the effects of age, race, sex and urbanicity, we found that the mortality rate in the total population slightly decreases with a one unit increase in the drought severity for all the timescales. However, this association was not statistically significant for any types of drought. We hypothesize that this might be due to heterogeneity in the association between drought and all-cause mortality in population sub-groups. This finding is in agreement with what Lynch et al. (2020) concluded for the whole United States. However, other studies have shown drought conditions significantly increases the mortality in the population (Salvador et al., 2020b; Salvador et al., 2021; Alam et al., 2021). Our results might be different 1) because of the different nature of the mortality data with annual counts and censored values, so we could not aggregate all mortality counts per county per year, 2) differences in study designs and study area, and 3) different drought exposure (both drought classification method in the study and the drought indicator selection). Unsimilar to other weather extremes such as heat waves, droughts can be quantified in multiple ways depending on the meteorological variables that the index has been calculated with or the different remote sensing products.

Drought is a complex phenomenon and affects many sectors such as agricultural and public health. Few existing literature suggests that drought does not affect everyone equally and some population sub-groups are more vulnerable than others (Salvador et al., 2020b; Lynch et al., 2020; Salvador et al., 2022).

Our findings demonstrate that female sub-populations in Nebraska were associated with increased mortality during drought in both metro and non-metro counties (Fig 3). White females aged 45-54 in non-metro counties were affected by all types of drought with mortality rates increasing by 1.016 [1.001,1.031], 1.013 [1.002,1.023], 1.016 [1.006,1.027] for short to long-term drought, respectively. Findings from recent studies in Brazil also showed a strong gender difference in these associations in female (Salvador et al., 2022). Other studies have also shown that women are more susceptible to the impacts of drought in the more rural communities for multiple reasons including, but not limited to, lower education, lower capacity to respond to drought, greater household responsibilities (Neumayer & Plümper, 2007; World Health Organization, 2014; IPCC, 2014; Hanigan et al., 2018). This finding conflicts with the findings of Hanigan et al. (2012), Salvador et al. (2021), and Lynch et al. (2020) who suggested that males are more affected by drought or that sex does not play a role in vulnerability. However, the location-specific nature and the differences in the study designs of these studies makes it difficult to generalize their results for populations in other regions.

Age was another risk factor in vulnerability to drought. Our analysis found significant association in age groups above 19. We only observed positive associations in white females aged 25-34 in metro counties, white females aged 45-54 in metro counties, white male and females aged 55-64, both in metro and non-metro counties. No other age group rendered a positive association between drought and all-cause mortality in Nebraska. There might be several pathways that drought affects these population sub-groups. For example, Figgs (2020) showed that the odds of an emergency department (ED) chronic bronchitis diagnosis among females was 3.77 times higher during the 2012 drought period compared to females admitted to the ED during the 2011 non-drought period. Unlike other studies (IPCC, 2014; Berman et al., 2017; Salvador et al., 2021), we did not find a significant increase in mortality in elderly groups (>65 in age). We found that mortality rate among white females aged >85 slightly decreases with an increase in drought severity. This protective effect might be partially due to the fact that there is less outdoor exposure for this age groups during drought (Lynch et al., 2020). White females aged 25-34 in metro counties constituted the most vulnerable population, with the highest IRR estimates with increasing drought severity. We also showed that this effect is higher in the short-term 1.054 [1.009,1.097], compared to long-term drought 1.027 [1.001,1.052]. However, the wide HPD interval reflects the statistical uncertainty that comes with this group's small sample size, so caution is needed in interpreting these results. According to our results, age groups 25-34 and 55-64 in metro counties and age group 45-54 in non-metro counties have the highest number of sub-groups at risk compared to other age groups. White men and women were the only sub-groups in these age categories showing positive association between mortality and drought exposure in all drought types and in both metro and non-metro counties. Unlike other recent studies, showing that children and elderly are more vulnerable to drought negative impacts (Salvador et al., 2021; Salvador et al., 2022), we found higher association between drought and drought exposure in 45-64 age groups in both metro and non-metro counties and the effect estimates for children and elderly age groups were negative.

Lynch et al. (2020) found that majority of increases in death associated with drought occurred within minority population sub-groups such as males other than black or white aged 55-64, black males aged 65-84. Our analyses on races other than white showed positive and negative association between mortality and drought exposure (Supplementary tables 1-3), however, we did not find any statistically significant positive association between drought and races other than white. This might be due to 1) population distribution in Nebraska which is dominantly white and 2) the low sample size in the sub-groups other than white and overwhelming number of zero mortalities in those groups (Table 1). We observed significant IRRs less than 1 only in black males between the age of 20-24 that could suggest a protective effect in these subgroups against drought. Similar to our results for the white females aged 25-34, these IRRs have large HPD intervals that reflects the uncertainty in these estimates and caution is needed in interpretation of these results.

Nebraska is an agricultural state with more than 90% of the area covered with grassland and cultivated crops with only a few urbanized areas mostly in the eastern part of the state. The population distribution is drastically uneven with more than 65% of population living in metro areas (Fig. 1). Most studies on health impacts on drought only focus on urban or rural and there is gap in the literature comparing the two environments in terms of health outcomes. In our study, we showed that urbanicity was not a significant covariate in our main model for the total population, however we still included the variable in our joint-stratification analyses based on age-race-sex-urbanity.

Finally, most studies on drought-related mortality and morbidity focus on measures that evaluate short-term drought exposure and more research is needed to evaluate the effects of longer-term droughts on human health. According to our results, longer term droughts (e.g.12-month EDDI measures) were associated with greater mortality rates compared to shorter-term droughts (e.g. 1- and 6-month EDDI measures). There are several proposed pathways that might explain these relationships. As heart disease and chronic lower respiratory disease are among the leading causes of mortality in the state, we hypothesize that long-term drought can worsen air quality and increase the likelihood of extreme heat events (Michelozzi et al., 2009; Peterson et al., 2013; Bell et al., 2018). Both air quality and extreme temperatures are known to be leading causes of climate-related mortality (Mitchell et al., 2016). We observed that in non-metro counties, white males and females aged between 45-54 are at significantly higher rate of mortality due to long-term drought. Non-metro counties in Nebraska could result in more environmental exposures associated with living in closer proximity to agricultural and natural landscapes. However, more cause-specific studies are needed to explain these findings. Longer droughts can create more favorable conditions for land degradation due to sustained water stress and longer depletion of soil moisture, and this can reduce air quality through increased dust storms, ozone, and other pollutants (Bell et al., 2015; Wang et al., 2017; Achakulwisut et al., 2018; Lambert et al., 2020; Lin et al., 2020). Longer droughts are also accompanied by more stable atmospheric patterns, including atmospheric blocking and high-pressure systems. These circulation patterns disrupt the zonal flow and cause the normal eastward progress of weather systems to stall. Atmospheric blocking and extended high pressure systems have been associated with heatwaves, wildfires, and increased air pollution (Pfahl & Wernli, 2012; Mazdiyasni & AghaKouchak, 2015; Dong et al., 2018). All these physical changes in the atmosphere have been linked to deleterious health outcomes (such as respiratory and circulatory issues) (Horton et al., 2010; Stanke et al.,2013; Bell et al., 2018; Salvador et al., 2020a; Sugg et al., 2020;). Individuals that were identified as white were most affected in terms of mortality, as we did not find any significant association in other races. However, this might be due to sample limitations, and not necessarily evidence of absent relationships.

To the knowledge of the authors, this is the first comprehensive study investigating the association between multiple types of drought and all-cause mortality in population sub-groups based on age-race-sex and urbanicity levels in Nebraska over a 35-year period. We also used a relatively new drought index of EDDI to quantify the drought exposure, though more comprehensive studies are needed to compare the performance of different drought indicators on health. Also, another strength of this study is the statistical analysis applying a zero-inflated censored negative binomial regression model with random intercept in the Bayesian framework. This statistical method allows us to account for censored mortality counts, large proportion of zero counts, and quantifying the spatial heterogeneity across counties in Nebraska.

This study has also potential limitations. Our mortality dataset was interval censored and this caused some restrictions in aggregating the sub-populations mortality counts to coarser groups to increase sample size. This was specifically problematic for "black" and "other" races in Nebraska, as they account for a small percentage of the total population. Also, to match the annual timescale of the mortality dataset, we created an annual drought index out based on the monthly EDDI values. This annual index might work for the shorter-term droughts that are most likely to happen within a specific year but might lead to underestimation of exposure to longer-term multi-year droughts that extend over a year. Drought duration and severity also play an important role on the health outcomes. Due to the annual structure of the data, we also could not include these criteria in our study. Drought also might have different impacts on health in different seasons. Heatwaves are more frequent during summer droughts and air pollution might be exacerbated during winter droughts atmospheric blocking patterns. The annual nature of the data did not allow us to account for seasonality in our statistical analysis. The coarse temporal resolution of the mortality dataset (annual) also prevented us from being able to control for other short-term environmental factors, such as temperature and air pollution, in our models. Finally, drought affect human health through multiple pathways such as cardiovascular or respiratory issues. This study only investigates the drought impact on all-cause mortality due to lack of access to specific causes of death.

5. Conclusions

Drought differs from other natural disasters as the health impacts can be overlooked by several primary exposures that tend to co-occur with drought (such as heatwaves and wildfires). According to the NOAA's Billion-Dollar Weather and Climate Disasters, between 1980 and 2021, 10 drought events affected Nebraska and these droughts have resulted in losses in many sectors such as health, economic, livestock, and energy (NCEI, 2022). Our retrospective study provides one of the first robust and comprehensive analyses of mortality based on age, race, sex, and urbanicity levels in Nebraska for a 35-year period. Overall, mortality slightly decreased with increase the same year drought severity for all the short to long-term droughts, however the result were not statistically significant. White population aged 25-34 and 45-64 in metro counties and 45-54 in non-metro counties were the population more at risk. We did not observe any positive association between all-cause mortality and drought exposure in any population sub-group besides white population. We also found protective effects in some population sub-groups including black males aged 20-24 and white females older than 85 in metro counties and white females aged 25-34 in non-metro counties. Our analysis also showed that longer-term droughts are associated with increased mortality in more sub-populations relative to shorter-term droughts collectively in metro and non-metro counties. These findings support that pathways to drought-related health outcomes are region and demographic group specific. Our results also show that it is crucial for public health practitioners to recognize the importance of drought duration in identifying outcomes. Future studies are needed to further understand these relationships.

Author contributions

Azar Abadi: Conceptualization, Methodology, Formal analysis, Software, Visualization Writing- Original draft preparation. **Yeongjin Gwon**: Conceptualization, Methodology, Software, Formal analysis. **Matthew Gribble**: Conceptualization, Methodology. **Jesse Berman**: Conceptualization, Methodology. **Rocky Bilotta**: Data Curation. **Mike Hobbins**: Conceptualization. **Jesse Bell**: Conceptualization, Methodology, Funding acquisition, Supervision.
All co-authors further contributed to writing – review and editing – of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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