Association between flooding and opioid overdose deaths in Appalachia

Fang J

Submitted: November 9, 2025, Revised: version 1, June 24, 2026, version 2, July 5, 2026
Accepted: July 9, 2026

Abstract
Flooding is increasingly recognized as a major public health threat, yet its potential relationship with opioid overdose mortality has received little quantitative investigation. This study examined whether severe flooding was associated with subsequent changes in opioid overdose deaths across counties in the Appalachian region of the United States, where overdose mortality has been disproportionately high. Counties experiencing severe flooding in 2011 were compared with non-flooded counties using a matched pre-post change analysis. Multiple propensity-score matching strategies (1:1, 1:2, 1:3, caliper, and full matching) were evaluated to improve comparability between groups, and multivariable linear regression models with robust standard errors estimated changes in average annual opioid overdose deaths between the three years before (2008–2010) and after (2012–2014) the flooding event. Across all matching approaches, estimated flooding effects remained positive, although statistical significance after full adjustment was retained only under the full-matching specification, which estimated approximately 1.75 additional overdose deaths per county over the post-flood period. Subgroup analyses suggested that the association was strongest among males, White populations, and adults aged 25–64 years. Because this observational study measured only the association between flooding and overdose mortality, the proposed mechanisms linking disaster-related disruption to increased overdose risk remain hypothetical and were not directly tested. These findings provide preliminary evidence that severe flooding may contribute to worsening opioid overdose outcomes in vulnerable communities and support incorporating substance-use considerations into disaster preparedness, response, and recovery planning.

Keywords
Opioid overdose, Flooding, Climate change, Natural disasters, Appalachia, Propensity score matching, Matched pre-post analysis, Environmental epidemiology, Disaster epidemiology, Health disparities

Joyce Fang, Montgomery Blair High School, 51 University Blvd E, Silver Spring, MD 20901, USA.
joyce.d.fang@gmail.com

https://doi.org/10.64336/001c.165257

1. Introduction

Flooding in the United States has been detrimental to many through social, economic, and health impacts. In fact, inland and riverine floods are the most common type of natural disaster, making flooding a nationwide problem (1). Flooding can have direct impacts through damage to homes, roads, and other infrastructure (2). A recent analysis estimated total annual flooding-related economic damages in the U.S. to be between US $179.8 billion and US $496.0 billion (2023 dollars) (3).

Beyond physical damage, flooding can also disrupt household economic welfare and well-being, including income, employment, public services, and the prices of goods and services. Several studies have shown that households with lower incomes are disproportionately affected by disasters due to reduced consumption capacity and financial resilience (4). Business interruption may also occur due to flood damage to business assets, with broader effects on supply chains and local economies (4). In addition, floods can contribute to displacement, environmental damage, and disruptions to both social support systems and community functioning (5).

Flooding is also associated with a wide range of adverse health outcomes. Immediate health risks include drowning and physical injury, while longer-term impacts may include cardiovascular disease, respiratory illness, and mental health disorders (6,7). Flooding may also interrupt access to healthcare services, further worsening health outcomes. Psychological distress following disasters has been widely documented and may have lasting impacts on well-being and behavior (5). These kinds of environmental shocks may also overlap with ongoing health crises, such as the increasing number of opioid overdose deaths.

Opioids, including prescription painkillers (e.g., oxycodone, hydrocodone, and morphine), synthetic opioids (e.g., fentanyl), and illegal drugs (e.g., heroin), affect the brain's reward system and can lead to addiction and overdose (8). Since the late 20th century, opioid addiction and overdose have become a major public health crisis in the United States, leading to widespread social, economic, and healthcare challenges. The opioid crisis was declared a public health emergency in 2017 and has been renewed in 2024 (9). Overdose deaths remain high, with more than 220 deaths per day and over 645,000 total deaths since the epidemic began (10).

The crisis is especially severe in rural regions. Appalachia, in particular, is an epicenter of the U.S. opioid epidemic, with overdose mortality rates significantly higher than the national average (11). Structural challenges in the region, including limited access to healthcare, transportation, education, and employment, may increase vulnerability to both substance use and external shocks such as natural disasters (12).

While flooding and opioid misuse may appear unrelated, the social, economic, and health disruptions caused by natural disasters may exacerbate substance use and overdose risk. However, there is limited empirical evidence quantifying this relationship at the county level.

This study examines the association between severe flooding and changes in opioid overdose deaths in Appalachia. Using matched pre-post change analysis, the study compares counties that experienced severe flooding in 2011 with those that did not. By focusing on changes in overdose deaths before and after the flooding event, this study provides new empirical evidence on the public health impacts of climate-related disasters.

2. Materials and Methods

2.1 Data

This study focuses on the Appalachian region, which spans 13 states from southern New York to northern Mississippi. The region had a population of 26.6 million in 2023 across 423 counties and 206,000 square miles (13).

This analysis focuses on the year 2011 when significant flooding occurred in Appalachia, including events associated with Tropical Storm Lee and Hurricane Irene (14). The year 2011 also represented the largest concentration of severe flooding events within the study period while allowing three-year pre- and post-event observation windows. Counties experiencing severe flooding in 2011, but not in other years during the 2000–2016 period, are classified as treatment counties. Those with no severe flooding during this period serve as control counties. Counties with flooding in years other than 2011 are excluded to ensure a cleaner comparison between treated and control groups.

Severe flooding events were identified using two datasets. The presidential disaster declarations (PDD) (15), from the Federal Emergency Management Agency (FEMA), served as the first dataset, as it was a formal process for securing federal assistance after disasters. Flood-related events identified through FEMA disaster declarations were then matched with extreme storm event data from the National Oceanic and Atmospheric Administration (NOAA) (16), which provide casualty information for each event. A PDD flooding event with casualties (deaths or injuries) was considered severe.

Of 423 counties in the Appalachian region, 36 counties that experienced a severe flood only in 2011 during the 2000–2016 period were identified as treatment counties (flooding = 1). A total of 204 counties that were not affected by flooding from 2000 to 2016 serve as control counties (flooding = 0). The remaining 180 counties were excluded from the analysis, as they experienced severe floods in years other than 2011.

County-level annual data on opioid-related deaths were collected from the CDC WONDER database from the Centers for Disease Control and Prevention (CDC) (17), which provides detailed demographics related to these deaths. Following a standard CDC practice, a combination of underlying death cause codes (X40-X44, X60-X64, X85, and Y10-Y14) and contributing death cause codes (T40.0-T40.4 and T40.6) were used to identify opioid-related overdose deaths.

Several government databases were used to obtain control variables. County-level population data were obtained from the U.S. Census in collaboration with the National Center for Health Statistics (NCHS) (18). County-level unemployment rate was determined using the Local Area Unemployment Statistics from the Bureau of Labor Statistics (BLS) (19). Poverty estimates and median household income were obtained from the Census Small Area Income and Poverty Estimates (SAIPE) Program (20), and education levels were determined using data from the American Community Survey across the years 2009 to 2013 (21).

2.2 Statistical methods

Statistical analyses were conducted in the R statistical environment (version 4.5.2) using RStudio (version 2024.04.2). Because counties experiencing severe flooding differed from non-flooded counties in several socioeconomic characteristics, propensity score matching was used to improve comparability between treatment and control groups and reduce confounding due to observed baseline differences. Analyses were performed using both the unmatched sample and matched samples to evaluate the robustness of the findings.

Propensity score matching was implemented using the *MatchIt* package (version 4.7.2). Counties experiencing severe flooding in 2011 were matched with counties that did not experience flooding during the 2000–2016 study period using nearest-neighbor matching. Four county-level socioeconomic variables measured prior to the post-flood observation period were used for matching: poverty rate, unemployment rate, percentage of adults without a high school diploma, and median household income. These variables were selected because they are established determinants of opioid overdose risk and may also influence county vulnerability to the health consequences of natural disasters.

Because no single matching algorithm is universally optimal, multiple matching strategies were evaluated, including 1:1, 1:2, and 1:3 nearest-neighbor matching, caliper matching, and full matching. Matching quality was assessed using the maximum standardized mean difference (Max SMD), with lower values indicating better covariate balance between flooded and non-flooded counties. Comparing results across multiple matching specifications allowed assessment of whether the estimated association was robust to different approaches for constructing comparable control groups.

The primary outcome was the change in the average annual number of opioid overdose deaths between the three-year period before the flooding event (2008–2010) and the three-year period after the event (2012–2014). Analyzing pre-post change scores reduces the influence of stable baseline differences between counties and focuses the analysis on changes occurring after the 2011 flooding event.

Linear regression models were estimated using the `lm()` function in the *stats* package. The primary exposure variable was a binary indicator identifying counties that experienced severe flooding in 2011. Models additionally adjusted for poverty rate, unemployment rate, median household income, educational attainment, and state fixed effects. HC1 heteroskedasticity-robust standard errors were calculated using the *sandwich* and *lmtest* packages because matching and weighting procedures may introduce heteroskedastic residual variance, making conventional ordinary least squares standard errors less reliable.

The estimated association between flooding and changes in opioid overdose deaths was examined across the unmatched sample and multiple matched samples. Robustness was evaluated by comparing regression coefficients, confidence intervals, and statistical significance across alternative matching specifications. Additional analyses were performed for demographic subgroups defined by sex, race, and age to investigate whether the observed association differed across populations.

2.3 Matched data

To generate matched data, counties that experienced severe flooding in 2011 were matched with counties that did not experience flooding during the 2000–2016 period using nearest-neighbor matching with the matchit() function in the MatchIt package. Matched datasets were then created using the match.data() function. Four variables from 2011 were used for matching: poverty percentage (poverty_pcti), unemployment rate (unemploy_ratei), percentage of the population without a high school diploma (edupct_lesshighi), and median household income (median_hhii).

Multiple matching strategies were evaluated, including 1:1, 1:2, and 1:3 nearest-neighbor matching, caliper matching, and full matching. Matching quality was assessed using the maximum standardized mean difference (Max SMD), where lower values indicate improved covariate balance between treated and control counties.

2.4 Linear regression

Linear regressions were performed on the unmatched and matched datasets to assess the association between flooding and opioid overdose deaths. HC1 heteroskedasticity-robust standard errors were used for the matched analyses to account for potential heteroskedasticity and unequal residual variance introduced by the matching procedures and weighting schemes.

The key independent variable, $flooding_i$, is a binary indicator equal to 1 if a county experienced severe flooding in 2011 and 0 otherwise. The dependent variable, $Change\_odd\_3year\_avg_i$, represents the change in the average annual number of opioid overdose deaths in county *i* during 2012-2014 (a three-year window post 2011) and during 2008-2010 (a three-year window before 2011). A positive value indicates an increase in overdose deaths after 2011.

The regression is specified as follows,

$$Change\_odd\_3year\_avg_i = b_1 * flooding_i + b_2 * poverty\_pct_i + b_3 * unemploy\_rate_i$$
$$+ b_4 * median\_hhi_i + b_5 * edupct\_lesshigh_i + state\_dummies_i + \epsilon_i$$

After estimating a relationship between the key independent variable ($flooding_i$) and the dependent variable ($Change\_odd\_3year\_avg_i$), robustness was assessed by examining the p-values and coefficients of all variables. Additionally, the relationship between the key independent variable (*$flooding_i$*) and the dependent variable (*$Change\_odd\_3year\_avg_i$*) was tested across different sub-populations. Additional analyses were performed on other control variables, including poverty percentage, unemployment rate, median household income, percentage of those with education less than high school graduation, and state dummies.

For all these regressions, the p-value, number of observations, and adjusted r-squared were recorded. Statistical significance was indicated using standard notation.

3. Results

3.1 Association between severe flooding and changes in opioid overdose deaths (unmatched sample)

Unmatched samples were first analyzed. Table 1 shows a positive association between severe flooding in 2011 and changes in opioid overdose deaths during the three years before and after the flooding event. The flooding variable remained positive across all model specifications, even as additional control variables were added, suggesting a positive association between severe flooding and the increases in opioid overdose deaths.

Table 1. Association between severe flooding (2011) and change in average annual opioid overdose deaths (2012–2014 vs. 2008–2010), overall population, unmatched sample.

Variable	(1)	(2)	(3)	(4)	(5) Fully Specified
Flooding (2011)	2.18** (0.91) [0.396, 3.964]	2.08** (0.91) [0.296, 3.864]	1.75* (0.90) [-0.014, 3.514]	1.89** (0.90) [0.126, 3.654]	1.83* (0.90) [0.066, 3.594]
Poverty (%)		-0.12* (0.06) [-0.238, -0.002]	4.61e-3 (0.07) [-0.133, 0.142]	0.13 (0.10) [-0.066, 0.326]	0.16 (0.10) [-0.036, 0.356]
Unemployment Rate (%)			-0.50*** (0.16) [-0.814, -0.186]	-0.42** (0.17) [-0.753, -0.087]	-0.41* (0.17) [-0.743, -0.077]
Median Household Income				1.3×10^{-4}* (6.8×10^{-5}) [-3.28×10^{-6}, 2.63×10^{-4}]	1.0×10^{-4} (7.1×10^{-5}) [-3.91×10^{-5}, 2.39×10^{-4}]
% Less Than High School					-0.09 (0.07) [-0.227, 0.047]
# of Obs.	240	240	240	240	240
Adjusted R^2	0.067	0.077	0.109	0.119	0.122

Notes: The dependent variable is the change in average annual opioid overdose deaths (2012–2014 vs. 2008–2010), for overall populations. All models are estimated using unmatched samples. State fixed effects are included in all specifications. Standard errors are in parentheses. 95% confidence intervals are shown in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

During the three-year window (2012-2014) following the flooding in 2011, the average treated county experienced approximately 1.8 more opioid overdose deaths per year than the average control county, suggesting a substantial increase in opioid overdose deaths associated with severe flooding (Table 1). Because the average population of the treated counties was approximately 66,000, this corresponds to roughly 2.7 additional deaths per 100,000 population.

The unemployment rate of a county in 2011 was negatively associated with the change in the average number of overdose deaths after vs. before 2011. One possible explanation is that counties with higher unemployment rates may have already experienced elevated opioid overdose mortality before 2011; thus, change in overdose deaths after 2011 could be smaller.

3.2 Matching results and robustness checks

Table 2 summarizes covariate balance across several matching specifications with full sample as a baseline. In the unmatched full sample, moderate imbalance remained between flooded and non-flooded counties (Max SMD = 0.22). Matching substantially improved balance across most specifications, with larger control-to-treated matching ratios generally producing lower standardized mean differences.

Table 2. Covariate balance across matching specifications.

Approach	Caliper	Treated	Controls	Max SMD
Full Sample	—	36	204	0.22
1:1 (No caliper)	No	36	36	0.36
1:2 (No caliper)	No	36	72	0.17
1:3 (No caliper)	No	36	108	0.10
1:1 (Caliper = 0.2)	Yes	35	35	0.32
1:2 (Caliper = 0.2)	Yes	35	69	0.21
1:3 (Caliper = 0.2)	Yes	35	103	0.15
Full Matching	—	36	204*	0.13

*Controls are retained with weights in full matching (effective sample size ≈ 121). Max SMD = maximum standardized mean difference. Lower values indicate better covariate balance.

Among the nearest-neighbor approaches, 1:1 matching nearest-neighbor algorithm resulted in the poorest balance (Max SMD = 0.36), even when compared to the unmatched sample. This is because each treated county was restricted to a single control, which resulted in several imperfect matches. Balance improved considerably when multiple matched controls were allowed (1:2 matching (Max SMD = 0.17) and 1:3 matching (Max SMD = 0.10)) by increasing the pool of comparable control counties. Caliper matching produced similar patterns but excluded one treated county because no suitable match was available within the specified caliper. Full matching also achieved strong covariate balance (Max SMD = 0.13) while retaining all observations through weighting.

Because no single matching approach is universally optimal, the association between severe flooding and opioid overdose deaths was examined using 1:2 matching, 1:3 matching, and full matching. As shown in Appendix Table A1, the estimated effects remained positive and statistically significant across all matching specifications, supporting the robustness of the findings.

Although 1:1 nearest-neighbor matching is commonly used as a baseline, it produced poorer covariate balance than the unmatched sample in this dataset. This likely reflects the limited availability of closely comparable control counties. Consequently, subsequent analyses focused on the better-balanced 1:2, 1:3, and full matching specifications.

3.3 Full regression models for matched samples

Table 3. Association between severe flooding (2011) and change in average annual opioid overdose deaths (2012–2014 vs. 2008–2010): matched samples

Variable	(1) 1:2 Matching (no caliper)	(2) 1:3 Matching (no caliper)	(3) Full Matching
Flooding (2011)	2.142 (1.378) [-0.596, 4.879]	1.606 (0.976) [-0.326, 3.538]	1.751** (0.790) [0.194, 3.308]
Poverty (%)	0.183 (0.133) [-0.080, 0.447]	0.162 (0.112) [-0.059, 0.383]	0.069 (0.099) [-0.127, 0.264]
Unemployment Rate (%)	-0.165 (0.348) [-0.856, 0.525]	-0.262 (0.256) [-0.770, 0.245]	-0.093 (0.155) [-0.400, 0.213]
Median Household Income	0.00028* (0.00015) [-0.00003, 0.00059]	0.00020* (0.00012) [-0.00004, 0.00044]	0.00007 (0.00009) [-0.00010, 0.00025]
% Less Than High School	0.108 (0.143) [-0.177, 0.392]	0.076 (0.103) [-0.127, 0.279]	-0.030 (0.058) [-0.144, 0.084]
Adjusted R^2	0.039	0.054	0.142

Notes: The dependent variable is the change in average annual opioid overdose deaths between 2012–2014 and 2008–2010. Models were estimated using 1:2 nearest-neighbor matching, 1:3 nearest-neighbor matching, and full matching. All models include state fixed effects. HC1 heteroskedasticity-robust standard errors are reported in parentheses. 95% confidence intervals are shown in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
[#]Full matching retains all observations with weights (effective sample size ≈ 121).

Table 3 presents fully adjusted regression models for the matched samples, controlling for poverty, unemployment, median household income, educational attainment, and state fixed effects. HC1 heteroskedasticity-robust standard errors were used in all models. The estimated association remained positive across all matching specifications and achieved statistical significance under the full matching approach. In the 1:2 and 1:3 matched samples, the estimated effects were 2.142 and 1.606 additional deaths per county, respectively, although these estimates were no longer statistically significant after adjustment for county socioeconomic characteristics and state fixed effects. Under full matching, severe flooding remained significantly associated with an increase of 1.751 opioid overdose deaths per county over the three-year post-flood period (robust SE = 0.790, 95% CI: 0.194 to 3.308, p = 0.028). Despite some variation in statistical significance, the estimated flooding effects were consistently positive and similar in magnitude across matching specifications. These findings were generally consistent with the results from alternative matching approaches presented in Appendix Table A1.

3.4 Flooding and change in overdose deaths before and after flooding: subpopulations

Table 4. Association between severe flooding and opioid overdose deaths across subpopulations

	Male	**Female**	**White**	**Nonwhite**	**<25**	**25–64**	**65+**
Panel A: 1:2 Matching							
Flooding	1.687*	0.579	2.235*	0.031	0.333	1.228**	0.144
Robust SE	(0.860)	(0.580)	(1.175)	(0.096)	(0.217)	(0.572)	(0.155)
95% CI	[-0.020, 3.395]	[-0.572, 1.730]	[-0.098, 4.568]	[-0.160, 0.222]	[-0.099, 0.764]	[0.093, 2.363]	[-0.164, 0.452]
Adjusted R^2	0.051	0.003	0.047	-0.003	0.024	0.074	-0.048
Panel B: 1:3 Matching							
Flooding	1.337**	0.552	1.868**	0.021	0.112	1.008**	0.113
Robust SE	(0.662)	(0.417)	(0.849)	(0.072)	(0.167)	(0.422)	(0.125)
95% CI	[0.027, 2.647]	[-0.273, 1.376]	[0.188, 3.547]	[-0.123, 0.164]	[-0.218, 0.441]	[0.173, 1.842]	[-0.134, 0.360]
Adjusted R^2	0.066	-0.006	0.058	0.003	0.006	0.109	-0.047
Panel C: Full Matching							
Flooding	1.225**	0.521	1.735**	0.012	0.089	0.942**	0.082
Robust SE	(0.578)	(0.379)	(0.731)	(0.070)	(0.137)	(0.366)	(0.112)
95% CI	[0.086, 2.364]	[-0.226, 1.269]	[0.294, 3.175]	[-0.125, 0.149]	[-0.181, 0.358]	[0.221, 1.663]	[-0.140, 0.303]
Adjusted R^2	0.173	0.037	0.144	0.021	0.133	0.196	-0.020
Panel D: Full Sample (No Matching)							
Flooding	1.278**	0.547	1.813**	0.012	0.058	0.885**	0.127
Robust SE	(0.631)	(0.362)	(0.783)	(0.067)	(0.147)	(0.389)	(0.117)
95% CI	[0.035, 2.520]	[-0.167, 1.260]	[0.270, 3.355]	[-0.119, 0.143]	[-0.232, 0.347]	[0.119, 1.651]	[-0.104, 0.358]
Adjusted R^2	0.144	0.019	0.109	0.017	0.047	0.151	-0.015

Notes: The dependent variable is the change in average annual opioid overdose deaths between 2012–2014 and 2008–2010 for demographic subpopulations. Models were estimated using 1:2 nearest-neighbor matching, 1:3 nearest-neighbor matching, full matching, and the unmatched full sample. All specifications include state fixed effects. HC1 heteroskedasticity-robust standard errors are reported in parentheses. 95% confidence intervals are shown in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4 presents subgroup analyses across matched and unmatched specifications to examine whether the association between severe flooding and opioid overdose deaths differed across demographic groups. Across the 1:2 matching, 1:3 matching, full matching, and unmatched full-sample specifications, the strongest and most consistent associations were observed among males, White populations, and adults aged 25–64. In the fully matched specification, severe flooding was associated with increases of 1.225 overdose deaths among males (robust SE = 0.578), 1.735 deaths among White populations (robust SE = 0.731), and 0.942 deaths among adults aged 25–64 (robust SE = 0.366). Similar effect sizes were observed across the alternative matching specifications and in the unmatched full sample.

In contrast, associations among females, non-White populations, individuals younger than 25 years, and adults aged 65 years or older were smaller and generally not statistically significant across specifications. Overall, the subgroup analyses suggest that the observed association between flooding and opioid overdose mortality was concentrated primarily among males, White populations, and working-age adults.

4. Discussion

4.1 Interpretation of the findings

This study found that Appalachian counties experiencing severe flooding in 2011 generally exhibited larger subsequent increases in opioid overdose deaths than counties that did not experience severe flooding during the study period. Although the estimated association remained positive across all matching strategies, statistical significance after full covariate adjustment was retained only under the full-matching specification. Consequently, the findings provide evidence consistent with an association between severe flooding and increased opioid overdose mortality while also illustrating the uncertainty inherent in observational analyses of relatively uncommon disaster events.

An important aspect of these findings is the consistency of the estimated flooding effect across multiple analytical approaches. Despite differences in statistical significance resulting from alternative matching specifications, the estimated flooding coefficient remained positive in every model. This consistency suggests that the observed relationship is unlikely to be an artifact of a single statistical method. At the same time, the variation in statistical significance demonstrates that the estimated association remains sensitive to analytical choices and should therefore be interpreted cautiously rather than as definitive evidence of causality.

4.2 Potential mechanisms

Several biologically and socially plausible mechanisms could explain the observed association. Flooding disrupts transportation networks, healthcare infrastructure, housing, employment, and community support systems simultaneously, creating conditions that may increase vulnerability among individuals with opioid use disorder. Climate-related disasters have been proposed to influence substance-use behaviors through multiple interacting pathways, including psychological stress, displacement, economic hardship, and interruption of healthcare services (22).

One important mechanism involves disruption of addiction treatment and recovery services. Individuals receiving medication-assisted treatment may temporarily lose access to clinics, pharmacies, harm-reduction programs, or counseling because of damaged infrastructure or transportation barriers. Experiences following Hurricane Sandy demonstrated that interruptions in opioid treatment services contributed to increased illicit drug use when patients were unable to obtain routine care (23). Similar disruptions following severe flooding could increase relapse risk and contribute to higher overdose mortality.

Flooding may also influence overdose risk indirectly through psychological and socioeconomic pathways. Loss of housing, financial instability, unemployment, and prolonged recovery efforts can increase depression, anxiety, and post-traumatic stress, all of which have been associated with greater vulnerability to substance misuse (22). These mechanisms are unlikely to operate independently; rather, healthcare disruption, economic hardship, and psychological stress may interact to amplify overdose risk following major disasters.

Importantly, however, none of these intermediary mechanisms were directly measured in the present study. Consequently, they should be viewed as biologically and socially plausible hypotheses supported by previous literature rather than explanations demonstrated by the current analysis.

4.3 Alternative explanations

Although the observed association is plausible, alternative explanations remain possible. Flooded and non-flooded counties may differ in ways that were not fully captured by the measured socioeconomic variables. Differences in healthcare capacity, opioid prescribing practices, illicit fentanyl availability, medication-assisted treatment access, or local public health policies could all contribute to variation in overdose mortality independent of flooding.

Furthermore, the opioid epidemic evolved rapidly during the study period as prescribing practices changed and synthetic opioids became increasingly prevalent. Although the matched pre-post change design reduces bias arising from stable baseline differences between counties, it cannot eliminate the possibility that temporal trends differed systematically between flooded and non-flooded regions. Accordingly, the findings should be interpreted as evidence of an association rather than confirmation of a causal relationship.

4.4 Comparison with previous literature

Previous research has established that flooding adversely affects physical health, mental health, healthcare access, and community functioning (1). Studies have also proposed conceptual frameworks linking climate-related disasters to increased substance-use disorders through disruptions in healthcare systems, economic instability, and psychological stress (22). However, quantitative evidence directly examining opioid overdose mortality following flooding has remained limited.

The present study extends this literature by applying propensity score matching and multivariable regression to estimate the association between severe flooding and subsequent changes in opioid overdose deaths at the county level. Although the observational design cannot establish causality, the results provide preliminary empirical evidence supporting a relationship that has previously been discussed largely through theoretical mechanisms rather than population-level analyses.

4.5 Implications for climate and public health
Climate projections indicate that extreme precipitation events and flooding are expected to become more frequent and more intense in many regions of the United States as the climate continues to change (1,24). Consequently, understanding the broader health consequences of flooding extends beyond disaster medicine to include chronic disease management, mental health, and substance-use disorders.

Disaster preparedness has traditionally emphasized evacuation planning, emergency response, and restoration of damaged infrastructure. The present findings suggest that maintaining continuity of addiction treatment, mental health services, harm-reduction programs, and overdose surveillance may also deserve consideration during disaster response and recovery. Because these recommendations are based on observational evidence, they should be viewed as precautionary public health measures rather than interventions supported by established causal evidence.

4.6 Scientific significance
The principal contribution of this study is not that it demonstrates flooding causes opioid overdose deaths. Rather, it identifies a reproducible statistical association that persists across multiple analytical approaches and generates a testable hypothesis regarding the indirect public health consequences of climate-related disasters. Establishing such associations is an important first step in scientific investigation because it identifies phenomena that warrant more detailed mechanistic study.

Future research should determine whether disruptions in healthcare access, medication-assisted treatment, economic stability, mental health, and community support systems account for the observed relationship. Direct evaluation of these intermediary processes will be essential for strengthening causal inference and identifying interventions capable of reducing overdose mortality following major flooding events.

4.7 Limitations
Several limitations should be considered when interpreting these findings. First, because the analysis focused on severe flooding events occurring in 2011, the results may not generalize to flooding events of different magnitude, duration, or geographic context. The limited number of treated counties also reduced statistical power, which may explain why some matching specifications produced positive but statistically non-significant estimates.

Second, although propensity score matching and multivariable regression reduced imbalance in measured socioeconomic characteristics, the observational nature of the study means that residual confounding cannot be excluded. County-level factors such as healthcare availability, opioid prescribing practices, illicit fentanyl availability, access to medication-assisted treatment, and local public health policies were not directly measured and may have influenced overdose mortality independently of flooding. Consequently, the observed association should not be interpreted as establishing a causal relationship.

Another limitation is that overdose deaths were analyzed as absolute counts rather than deaths per 100,000 population. Although the analysis focused on changes in overdose mortality within counties over time, using normalized mortality rates would improve comparisons across counties with different population sizes.

Because this study was conducted at the county level, the findings represent ecological associations and cannot be interpreted as demonstrating that individuals directly exposed to flooding experienced a higher risk of opioid overdose. Individual-level studies are needed to determine whether the observed county-level patterns reflect individual behavioral and health outcomes. Additionally, the study was limited to the Appalachian region, and the findings may not be generalizable to other regions of the United States with different demographic, socioeconomic, or healthcare characteristics.

Finally, the manuscript proposes a multi-step pathway in which flooding leads to infrastructure disruption, reduced healthcare access, economic hardship, psychological stress, increased opioid misuse, and ultimately increased overdose mortality. However, the present study directly measured only the association between flooding and overdose deaths; none of the proposed intermediary mechanisms were empirically evaluated. While this causal pathway is biologically and socially plausible, it remains hypothetical within the context of this study. Future research should directly measure these intermediary processes to determine whether they explain the observed association and to strengthen causal inference.

4.8 Future research

Future research should evaluate flooding events across multiple years and geographic regions to determine whether the observed association is reproducible under different disaster scenarios and population settings. Expanding the analysis beyond a single flooding event would improve statistical power and allow assessment of whether the magnitude of the association varies with flood severity, duration, or frequency.

Future studies should also strengthen causal inference by incorporating normalized overdose mortality rates, additional county-level confounders (such as healthcare availability, opioid prescribing patterns, and socioeconomic vulnerability), and modern causal inference methods including inverse probability weighting or doubly robust estimators. Longitudinal analyses with repeated post-disaster observations could further characterize both the short-term and long-term effects of flooding on overdose mortality.

Most importantly, future research should directly evaluate the hypothesized mechanisms linking flooding to opioid overdose deaths.

Measuring disruptions in healthcare access, medication-assisted treatment, economic hardship, housing instability, mental health outcomes, and social support systems would help determine which intermediary pathways contribute most to overdose risk following natural disasters. Such studies would move beyond demonstrating statistical association toward identifying the mechanisms through which climate-related disasters influence substance-use outcomes.

4.9 Implications and possible policy changes

Although this observational study cannot establish causality, it suggests that severe flooding may represent an additional risk factor for worsening opioid overdose outcomes in vulnerable communities. Disaster preparedness planning has traditionally focused on preventing immediate injuries and restoring physical infrastructure. The present findings indicate that maintaining continuity of addiction treatment, mental health services, and harm-reduction programs may also deserve consideration during disaster response and recovery.

Flood-related disruptions to transportation, healthcare access, housing, and local economies may disproportionately affect individuals with opioid use disorder by interrupting access to medications, treatment programs, and social support networks. Emergency preparedness plans could therefore incorporate strategies to preserve access to medication-assisted treatment, overdose prevention resources such as naloxone, behavioral health services, and recovery support throughout disaster response and recovery periods.

These findings also highlight the importance of integrating public health surveillance with disaster management. Monitoring overdose trends following major flooding events could help identify communities experiencing elevated risk and allow public health agencies to deploy targeted interventions more rapidly. Because the mechanisms underlying the observed association remain untested, these recommendations should be viewed as precautionary measures rather than evidence-based responses to a confirmed causal relationship.

Finally, as climate change is expected to increase the frequency and intensity of extreme precipitation and flooding events, understanding the broader health consequences of natural disasters will become increasingly important. Future research that directly measures healthcare disruption, economic hardship, mental health outcomes, and substance-use behaviors following disasters will help determine which interventions are most effective at reducing overdose mortality.

5. Conclusion

This study examined whether severe flooding was associated with subsequent changes in opioid overdose mortality across Appalachian counties using a matched pre-post change analysis. Across multiple matching strategies, estimated flooding effects remained consistently positive, although statistical significance after full covariate adjustment was retained only under the full-matching specification. These findings suggest that severe flooding may contribute to increases in opioid overdose mortality, while also illustrating the challenges of estimating disaster-related health effects from observational county-level data.

Because this study measured only the association between flooding and overdose deaths, the intermediate mechanisms linking disaster exposure to overdose risk—including disruptions in healthcare access, economic instability, and psychological stress—remain untested. Consequently, the results should be interpreted as evidence of an association rather than confirmation of the proposed causal pathway.

Future studies should evaluate flooding events across multiple regions and years, incorporate overdose rates in addition to absolute counts, and directly measure the hypothesized intermediary mechanisms responsible for increased overdose risk. Such work would strengthen causal inference and improve understanding of how climate-related disasters influence substance-use outcomes.

Despite these limitations, this study provides preliminary quantitative evidence that severe flooding may have broader public health consequences extending beyond immediate physical injury. Integrating substance-use prevention, continuity of addiction treatment, and mental health services into disaster preparedness and recovery planning may help reduce overdose risk in vulnerable communities following major flooding events.

Acknowledgement
I would like to express my sincere gratitude to Professor Zhen Lei, Professor of Energy and Environmental Economics at the Department of Energy and Mineral Engineering, Pennsylvania State University, for his invaluable guidance, support, and encouragement throughout my study and research.

6. References

1. Union of Concerned Scientists. (n.d.). *Climate change, extreme precipitation and flooding*. https://www.ucs.org/resources/climate-change-extreme-precipitation-and-flooding

2. U.S. Environmental Protection Agency. (2016, August). *Climate change indicators: River flooding*. https://www.epa.gov/climate-indicators/climate-change-indicators-river-flooding

3. United States Joint Economic Committee. (2024, June 10). *Flooding costs the U.S. between $179.8 and $496.0 billion each year*. https://www.jec.senate.gov/public/index.cfm/democrats/2024/6/flooding-costs-the-u-s-between-179-8-and-496-0-billion-each-year

4. Allaire, M. (2018). Socio-economic impacts of flooding: A review of the empirical literature. *Water Security, 3*, 18–26. https://doi.org/10.1016/j.wasec.2018.09.002

5. Stanke, C., Murray, V., Amlôt, R., Nurse, J., & Williams, R. (2012). *The effects of flooding on mental health: Outcomes and recommendations from a review of the literature*. *PLOS Currents, 4*, e4f9f1fa9c3cae. https://doi.org/10.1371/4f9f1fa9c3cae

6. Du, W., FitzGerald, G. J., Clark, M., & Hou, X.-Y. (2010). Health impacts of floods. *Prehospital and Disaster Medicine, 25*(3), 265–272. https://doi.org/10.1017/S1049023X00008141

7. Dee, J. E. (2023, December 14). *Study reveals the human health costs of exposure to floods*. Yale School of Public Health. https://ysph.yale.edu/news-article/ysph-study-reveals-the-human-health-costs-of-exposure-to-floods/

8. Centers for Disease Control and Prevention. (2025, June 9). *About overdose prevention*. https://www.cdc.gov/overdose-prevention/about/index.html

9. Administration for Strategic Preparedness and Response. (2024, June 25). *Renewal of determination that a public health emergency exists nationwide as a result of the continued consequences of the opioid crisis*. U.S. Department of Health and Human Services. https://aspr.hhs.gov/legal/PHE/Pages/Opioid-25June2024.aspx

10. Centers for Disease Control and Prevention. (2025, June 9). *Understanding the opioid overdose epidemic*. https://www.cdc.gov/overdose-prevention/about/understanding-the-opioid-overdose-epidemic.html

11. Moody, L. N., Satterwhite, E., & Bickel, W. K. (2017). Substance use in rural Central Appalachia: Current status and treatment considerations. *Journal of Rural Mental Health, 41*(2), 123–135. https://doi.org/10.1037/rmh0000064

12. Appalachian Regional Commission. (n.d.). *Addressing substance use disorder in Appalachia*. https://www.arc.gov/addressing-substance-abuse-in-appalachia/

13. Appalachian Regional Commission. (n.d.). *About the Appalachian region*. https://www.arc.gov/about-the-appalachian-region/

14. National Weather Service. (n.d.). *4th anniversary of the flooding from Tropical Storm Lee*. National Oceanic and Atmospheric Administration. https://www.weather.gov/ctp/TSLeeFlooding

15. Federal Emergency Management Agency. (2025). *Disaster declarations summaries – v2*. https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v2

16. National Centers for Environmental Information. (n.d.). *Storm Events Database*. National Oceanic and Atmospheric Administration. https://www.ncei.noaa.gov/stormevents/

17. Centers for Disease Control and Prevention. (n.d.). *CDC WONDER*. https://wonder.cdc.gov/

18. National Center for Health Statistics. (n.d.). *Bridged-race population estimates*. CDC WONDER. https://wonder.cdc.gov/bridged-race-population.html

19. U.S. Bureau of Labor Statistics. (n.d.). *Local area unemployment statistics: Tables and maps*. https://www.bls.gov/lau/tables.htm

20. U.S. Census Bureau. (n.d.). *Small Area Income and Poverty Estimates (SAIPE): Datasets.* https://www.census.gov/programs-surveys/saipe/data/datasets.html

21. U.S. Census Bureau. (n.d.). *American Community Survey (ACS).* https://www.census.gov/programs-surveys/acs.html

22. Vergunst, F., Berry, H. L., Minor, K., & Chadi, N. (2023). Climate change and substance-use behaviors: A risk-pathways framework. *Perspectives on Psychological Science, 18*(4), 936–954. https://doi.org/10.1177/17456916231159230

23. Zolopa, C., Hoj, S., Bruneau, J., Meeson, J.-S., Minoyan, N., Raynault, M.-F., Makarenko, I., & Larney, S. (2021). A rapid review of the impacts of "Big Events" on risks, harms, and service delivery among people who use drugs: Implications for responding to COVID-19. *International Journal of Drug Policy, 92*, Article 103127. https://doi.org/10.1016/j.drugpo.2021.103127

24. Intergovernmental Panel on Climate Change. (2021). *Climate change 2021: The physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. https://doi.org/10.1017/9781009157896

Appendix

Table A1. Comparison of matching approaches for the association between severe flooding (2011) and change in average annual opioid overdose deaths (2012–2014 vs. 2008–2010)

Approach	Max SMD	Treated	Controls	Estimate	Robust SE	p
Full Sample	0.22	36	204	1.824	0.811	0.026
1:1 (No caliper)	0.36	36	36	3.772	1.971	0.061
1:2 (No caliper)	0.17	36	72	2.266	1.213	0.065
1:3 (No caliper)	0.10	36	108	1.888	0.880	0.034
1:1 (Caliper = 0.2)	0.32	35	35	3.772	1.977	0.062
1:2 (Caliper = 0.2)	0.21	35	69	2.270	1.219	0.066
1:3 (Caliper = 0.2)	0.15	35	103	1.918	0.893	0.034
Full Matching	0.13	36	204*	1.747	0.761	0.023

*Controls are retained with weights in full matching (effective sample size ≈ 121). Max SMD = maximum standardized mean difference. Lower values indicate better covariate balance. Robust SE = heteroskedasticity-robust (HC1) standard error.