

Emergency Department Utilization and Unplanned Hospitalizations Associated with Floods in
the US from 2008-2017: An Interrupted Time Series and Cohort Analysis

Zachary S. Wettstein

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Committee:

Joel D. Kaufman

Jeremy J. Hess

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Zachary S. Wettstein

University of Washington

Abstract

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Zachary S. Wettstein

Chair of the Supervisory Committee:

Joel D. Kaufman

Department of Epidemiology

Background: Flooding is a major environmental hazard, with events increasing in intensity and frequency in the context of anthropogenic climate change. Significant health and economic impacts result from floods, particularly among vulnerable populations. However, comprehensive analyses of the health consequences of flooding, especially in terms of healthcare utilization and associated costs in the United States, remain limited.

Methods: This retrospective study analyzed a decade of data (2008-2017) to assess the impact of large-scale flood events on healthcare utilization among Medicare beneficiaries over age 65 in the United States. Using the Multi-sourced Flood Inventories (MFI) for flood exposure assessment, the study employed an interrupted time series analysis and a conditional fixed-effects regression approach to explore the incidence of emergency department (ED) visits and

hospital admissions pre- and post-flood. Healthcare costs associated with these events were also evaluated, standardized to 2017 USD.

Results: The analysis encompassed over 11.8 million Medicare beneficiaries, revealing a statistically significant increase in healthcare utilization following flood exposure. The rate of all-cause ED visits and hospital admissions rose by 4.8% and 7.4%, respectively. Cost analysis indicated an average increase of \$17 per exposed individual in Medicare-reimbursed healthcare expenses post-flood and a cumulative increase of over \$261 million in national healthcare costs attributable to flooding. Stratified analyses highlighted greater impacts on certain demographic groups, including adults over 85 years, and specific seasonal patterns.

Conclusions: Our findings demonstrate a clear association between flood exposure and increased healthcare utilization and costs, underscoring the need for targeted public health strategies and improved disaster preparedness, especially for older adults. This study contributes to a more comprehensive understanding of the health-related costs of flooding, informing future climate change resilience and healthcare planning.

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Introduction

Flooding accounts for about 40 percent of all global natural disasters, the most common environmental hazard in the world.¹⁻³ Flooding results in considerable morbidity and mortality, accounting for up to 50% of all deaths due to natural disasters.^{1,2} The United States is no exception, with most disaster-related deaths due to drowning in floodwaters.¹ Floods are some of the costliest disasters in the US, many resulting in over \$1 billion in damages, with the majority of these extremely damaging floods occurring in the past decade alone.^{4,5} These estimations reflect the direct costs of infrastructure damage and business losses and do not include the costs associated with healthcare use, morbidity, or mortality, and therefore underestimate the societal costs associated with flooding. The limited analyses that have been done have found that flooding has among the highest per capita health damages of all disasters in the US.⁶

Floods occur when water breaches the confines of natural or human-made bodies of water, and are caused by rainfall, melting snow or ice, or failure of water-containing structures. The frequency and intensity of extreme precipitation events have increased over the past century and are expected to increase further with climate change, resulting in a greater risk of flooding.⁷ Exceptional precipitation in 2018 contributed to damaging floods in the mid-Atlantic region and was made 1.1 to 2.3 times more likely by anthropogenic climate change.⁸ Projections for flood exposure later in the century show significant increases in population exposure under both moderate and high emissions scenarios, and annual property damages under a high emissions scenario are approximately \$4 billion greater than under a low emissions scenario by the end of the 21st century.^{9,10}

Risk of exposure to flooding is influenced by geographic proximity, environmental factors, and political and commercial activities, whereas vulnerability to flooding is greatly affected by socioeconomic, demographic and population health factors.¹¹ Effects of flooding are not evenly distributed: during flood events, females, children and elderly appear to be at greatest risk of psychological and physical health effects, whereas young men appear to be at greatest risk of mortality.^{2,11}

Flooding affects health via a myriad of pathways. Direct health consequences of floods include drowning, injuries related to debris and chemical contaminants, electrical injuries and hypothermia.¹²⁻¹⁴ Indirect health consequences result from the damage incurred on physical structures resulting in exposure to infectious diseases, contaminated water, disruptions of health services, and human displacement.^{14,15} The time course of health impacts ranges from immediate impacts such as drowning, hypothermia, and injury, to longer-term impacts including exacerbations of chronic disease and mental health, prolonged exposure to contaminated drinking water and flood-damaged homes.^{14,16}

Efforts to quantify the health impacts of flooding in the US have been limited; inconsistent reporting has resulted in an underreporting of non-fatal injuries and health impacts.² One study found that the 2009 Red River flood in North Dakota resulted in 2 deaths, 43 hospitalizations, and 263 emergency department (ED) visits and normalized health damages of \$145,495 per 1,000 people exposed, among the highest disaster-specific health damage rate estimates.⁶ Another recent analysis examined mortality associated with inland flooding in the US using validated social vulnerability indicators for mortality and property damage related to flooding in the US from 2008 to 2012.¹⁷ This study included a total of 283 deaths and found several social vulnerability factors that predicted deaths and property damage,

including rurality, poverty, and ethnic minority status. This analysis did not evaluate the non-fatal health impacts associated with flooding however, and as a result, underestimates the human health consequences.

On a smaller scale and employing a case-crossover design, two studies in Massachusetts found an association between flood exposure and gastrointestinal illness and *Clostridium difficile* infection.^{18,19} Similar methods have not been implemented on a broader scale or for other health conditions. Improved damage estimates that link flooding with other health impacts are needed in the field of climate and health.^{20–22} Limited understanding of the associations between flooding and acute and sub-acute health outcomes limits health impact assessment, risk communication, and projection of climate change health impacts, all of which are needed to clarify climate change risks to human health and to increase resilience to climate-related flooding events through disaster risk reduction efforts.^{23,24}

To address these gaps in our understanding of the health impacts of flooding, our study aims to provide a comprehensive analysis of the relationship between large-scale flood events and healthcare utilization among Medicare beneficiaries over age 65 in the US. Utilizing a decade-long dataset, we examine the incidence of ED visits and hospital admissions in the wake of flooding, alongside a detailed assessment of associated healthcare costs. This analysis not only seeks to quantify the immediate and short-term health impacts of floods but also to explore potential variations across demographic groups and flood-related factors. By employing a methodological framework that includes interrupted time series analysis (ITSA) and a conditional fixed-effects regression approach, our study endeavors to enhance the current understanding of flood-related health burdens and inform future public health preparedness in an era of increasing hydrological variability and climate change.

Methods

Study design

The study employed a retrospective design using administrative data, with two separate analyses for healthcare utilization. Analysis 1 was a quasi-experimental design with an ITSA approach to explore the population-level impacts and hazard period duration and was used to validate the time periods used in Analysis 2. Analysis 2 was a community-level analysis of a cohort of Medicare beneficiaries living in flood-exposed ZIP code tabulation areas (ZCTA) in the 4 weeks before and after flood onset, conducted on the ZCTA-level.

Flood exposure assessment was determined using the Multi-sourced Flood Inventories (MFI), as described below.^{25,26} Flood start date from the MFI and the flooded ZCTA were used to identify the spatiotemporal extent of the flood, and Medicare beneficiary home addresses were used to attribute flood exposure to individual beneficiaries. Medicare claims data and associated discharge diagnoses, for ED visits and hospital admissions (HA), categorized into cause-specific and all-cause diagnoses, were used for outcomes. For Analysis 1, all-cause diagnoses and a select number of cause-specific diagnoses were used (Table 1). For Analysis 2, all-cause diagnoses and a broader range of cause-specific diagnoses were used (Table 2). Costs associated with these Medicare claims were tabulated on the 4-week flood hazard and control periods as with Analysis 2 and used for the analysis of healthcare costs, standardized to 2017 US Dollars (USD). The Centers for Disease Control and Prevention (CDC) county-level Social Vulnerability Index (SVI) was an additional covariate incorporated in the stratified analysis.

Study setting

The study setting was the Continental United States (CONUS) from January 1, 2008, through December 31, 2017. ZCTA included in the analysis were those reported by the MFI to have been flooded during that period.

Study subjects

Study subjects were enrolled Medicare beneficiaries aged 65 years and older living in ZCTA experiencing floods as reported in the MFI during the study period above. Medicare beneficiaries under age 65 years were excluded from the analysis due to small sample size and the unique eligibility criteria for this age group. Unlike the general population over 65 years, younger adults qualify for Medicare enrollment due to specific diagnoses (end-stage renal disease, amyotrophic lateral sclerosis, or at least 24 months of receiving Social Security Disability Insurance), thereby constituting a distinct population with different health status than the general population of adults or those over 65 years.²⁷ No other exclusionary criteria were applied. The cohort used in Analysis 2 was comprised of all Medicare beneficiaries living in the flooded ZCTA in the year of the ZCTA flood.

Data sources

Numerous sources of data were used in this analysis. Flooding data were sourced from the Multi-sourced Flood Inventories (MFI), an open-access database of flood events in the CONUS from 1998-2019. The MFI aggregates data from stream gauge observations, remote sensing, and model simulation to generate the most comprehensive, open-access, geospatial database of floods currently available.^{25,26} For a flood to qualify for inclusion in the MFI, it exceeded a 20-year return period, meaning the average number of years between a flood of this magnitude was 20 years, and therefore meeting a location-specific threshold of flood intensity. The floods in the MFI are reported on the sub-catchment level, a hydrological unit of land with a natural boundary where all surface water drains to a common channel or point. These sub-catchment data were converted to ZCTA-level floods for linkage with the Medicare beneficiary data. Flood extent was estimated by calculating the maximum surface area of contiguous ZCTA flooded in the same event, and corresponding quartiles were used for stratification in Analysis 2. Medicare beneficiary data were sourced from the Centers for Medicare and Medicaid services, providing individual-level healthcare encounters including discharge diagnoses, cost of claims, and demographic data. Daily counts of encounters and corresponding diagnoses and costs were provided on an individual level in the 4-weeks before and after flood onset for each flooded ZCTA. County-level composite SVI values were acquired from the CDC and corresponding ZCTA-level composite SVI values were used to calculate SVI quartiles for stratification in Analysis 2.

Data analysis

Analysis 1

An ITSA using a Poisson regression was performed on a range of multi-week periods before and after flood onset across all flooded ZCTA.²⁸ All-cause ED visits and HA, and certain cause-specific diagnoses for gastrointestinal illness (GI) and mental health (MH) conditions (Table 1) were aggregated by week and used for the ITSA. The ITSA was performed using 2-, 4-, 6-, and

8-week periods before and after the flood to evaluate the temporal relationship between flood exposure and healthcare utilization. ZCTA-level flood data were used in the analysis, aggregated on a national level. A Poisson regression was used to estimate the relative risk (RR) and 95% confidence interval (CI) of a particular healthcare utilization type in the flood period compared to the pre-flood period.

ITSA model specification for weekly count of healthcare utilization events (Y_T):

$$\text{Log}(E(Y_T)) = \beta_0 + \beta_1 \text{Time} + \beta_2 \text{Flood} + \beta_3 \text{TimeSinceFlood}$$

where β_0 represents the baseline level of healthcare utilization, β_1 is the trend of healthcare utilization before the flood start, β_2 is the immediate change in the level of healthcare utilization at the start of the flood, and β_3 is the change in slope after the flood (interaction term).

Analysis 2

A ZCTA-level analysis was performed among a cohort of exposed older Medicare beneficiaries for total all-cause and cause-specific diagnostic categories for ED visits and HA (Table 2). Based upon the findings from Analysis 1, beneficiaries were included in the cohort if they resided in a flooded ZCTA in the 4-week period before and after flood onset. A fixed-effects conditional negative binomial regression model was performed using total counts of all-cause and cause-specific encounters during the pre- and post-flood periods to estimate incident rate ratios (IRR) and 95% confidence intervals, conditioning on the ZCTA. Model terms included flood exposure and a log-offset of the Medicare beneficiary population within a given ZCTA and was specified as follows:

$$\text{Log}(E(Y_T)) = \beta_0 + \beta_1 \text{Flood} + \log(\text{ZCTA Medicare Population})$$

where β_0 represents the baseline level of healthcare utilization, β_1 is the coefficient for flood period, and ZCTA Medicare Population is the size of the Medicare population within a given ZCTA.

A stratified analysis was conducted on sex, age category (65-74 years, 75-84 years, and 85 years and above), race (White, Black), flood season (winter, spring, summer, fall), quartile of flood extent, and quartile of composite SVI, to evaluate for potential effect modification.

The IRR and 95% confidence intervals were calculated based upon the β_1 coefficient from the stratified analysis. The attributable risk percentage (AR%) for each outcome type was calculated based on the IRR and the number of excess visits attributable to flood exposure were calculated by multiplying the AR% by the number of the specific visits in the flood period.

Cost analysis

To assess the economic impact of large flood events on healthcare utilization, we conducted a comprehensive cost analysis using three distinct methodologies, with all costs standardized to 2017 USD values. The first approach employed a paired t-test at the individual beneficiary-level to compare the cost of Medicare claims in the 4-week periods before and after flood onset and estimate individual-level costs. A second analysis utilized a conditional fixed-effects linear regression methodology conditioning on ZCTA, where ZCTA-level costs were estimated using ordinary least squares regression with a logged ZCTA population offset. The model specification is as follows:

$$\text{Cost} = \beta_0 + \beta_1 \text{Flood} + \log(\text{ZCTA Medicare Population})$$

where β_0 represents the baseline level of healthcare costs, β_1 is the coefficient of the flood period, and ZCTA Medicare Population is the size of the Medicare population within a given ZCTA.

Finally, to consider the financial impact system-wide, the results from the AR% analysis of excess ED visits and HA due to flood exposure were multiplied by the average cost per Medicare visit type and age over 65 years in 2017 USD according to the US Agency for Healthcare Research and Quality (AHRQ) (\$690 for ED visits, \$14,700 for hospitalizations).^{29,30}

Results

Flood exposure data

In the period from 2008 through 2017, there were 16,536 flooded ZCTA from among 33,140 total ZCTA in the US, with 8,918, or 26.9%, of all ZCTA uniquely flooded. The median and mean number of floods experienced by flooded ZCTA were 1 (IQR 1 - 2) and 1.46 (SD 1.09), respectively. The median flood duration was 10 days (IQR 4 - 30) and mean 21.6 days (SD 30.64). The median area flooded was 34,769 square-miles (IQR 17,319 - 65,584). The median number of Medicare beneficiaries per flooded ZCTA was 4,142 (IQR 2,006 - 7,536).

There was monthly and annual variability in flood frequency and duration (Table 3). Floods were most frequent in May, with 3,628 ZCTA floods, whereas the fewest were observed in November, with 112 ZCTA floods. The greatest number of floods occurred in 2015 (3,108 ZCTA floods), while the fewest floods occurred in 2009 (942 ZCTA floods), with a median duration ranging from 5 days in 2010 to 35 days in 2014.

Geographically, the floods occurred throughout the CONUS, with a predominance in the South, Midwest, and Mountain West, with no region unaffected by floods (Figure 1). Most flooded ZCTA experienced 1 flood, while the South, Midwest and Mountain West were the regions with ZCTA affected by multiple floods. This pattern was more pronounced when visualizing the duration of flooded days (Figure 2), shown by quintile of flood duration, illustrating a similar geospatial distribution of floods.

Cohort description

Over 11.8 million Medicare beneficiaries 65 years and older were included in the cohort (Table 4). This cohort had a mean age of 74.4 years, a female predominance (56.3%), and the vast majority identifying as White (88.3%) or Black (7.5%). The mean ZCTA flood exposure per beneficiary was 1.3 (standard deviation 0.6).

Analysis 1

The ITSA was performed on the 2-, 4-, 6-, and 8-week periods before and after flood start date and 16,536 flooded ZCTA were included in the analysis. The relative risk (RR) and 95% confidence intervals (CI) of healthcare utilization after flood onset, stratified by period duration in weeks, is shown in Table 5. Across all durations of the ITSA, there was a statistically significant increase in risk of ED visits for all-cause and GI diagnoses of a similar magnitude across

durations – for all-cause ED visits at 8 weeks, RR of 1.013 (95%CI: 1.009-1.018). No statistically significant association was seen with inpatient hospitalizations for all-cause or cause-specific diagnoses however, as noted in the Figure 3, the increase in ED visits was noted upon start of the flood while the RR of inpatient admissions demonstrated a trend towards significance during longer hazard period duration in weeks.

Analysis 2

The results of the ZCTA-level analysis of all-cause and cause-specific outcomes across the study period for ED visits and HA are shown in Table 6. Across nearly all outcomes except for ED mental health visits, the IRR and 95% confidence intervals demonstrated statistically significant increases in healthcare utilization when comparing the flood hazard period to the control period. Among older adult Medicare beneficiaries exposed to a flood, the rate of all-cause ED visits increased by 4.8% (IRR 1.048, 95%CI: 1.043-1.053) and all-cause hospitalizations increased by 7.4% (1.074, 1.067-1.081). The greatest magnitude increase in the IRR was observed for metabolic and renal conditions among ED visits (1.084, 1.062-1.106) and injuries (1.051, 1.039-1.062) and among hospitalizations, for infectious disease (1.117, 1.101-1.133) and metabolic and renal conditions (1.095, 1.068-1.122). Attributable risk percentages (AR%) were calculated from the IRR and ranged from 3.1% for ED gastrointestinal visits up to 7.7% for metabolic and renal conditions. For hospital admissions, the AR% ranged from 6.4% of cardiovascular admissions attributable to the flood exposure up to 10.5% of infectious disease admissions. Using the overall count of these cause-specific and all-cause visits and the AR%, excess attributable visits were calculated and shown in Table 6, with 21,265 excess ED visits and 16,787 HA attributable to the flood exposure. These values were used subsequently in the cost analysis as outlined below.

A stratified analysis was performed along multiple variables, with results shown in Table 7 and Figure 4 for all-cause ED visits and HA, with calculated IRR and associated 95% confidence intervals as well as attributable risk percentages and excess attributable visits in the study period. Sex-stratified results revealed an increased rate of ED visits (1.052, 1.045-1.059) and HA (1.084, 1.07-1.093) among males compared to females with overlapping confidence intervals. Age-stratification demonstrated increasing IRR with increasing age categorization, with increased rate of utilization of 4.9% for HA among adults 65-74 years (1.049, 1.039-1.059), 7.3% higher among adults 75-84 (1.073, 1.063-1.084), and 12.4% greater among adults 85 years and above (1.124, 1.11-1.138), with non-overlapping confidence intervals. The IRR for ED visits demonstrated a similar trend and statistical significance albeit with a lower magnitude. Race-stratification was also performed by identification as White or Black only due to limited sample sizes among other racial categories, with results demonstrating higher IRR among beneficiaries identifying as Black compared to White with overlapping confidence intervals.

Stratified analyses were also performed on flood characteristics including the season in which the flood started and the quartile of flood area, to evaluate for effect modification by seasonality or extent. The season-stratified results demonstrated increased IRR for ED visits (1.067, 1.056-1.077) and HA (1.111, 1.097-1.126) in the summer months, for which the confidence intervals did not overlap with spring but did with other seasons. Other seasons did not show statistically significantly different results from one another, which all had overlapping confidence intervals. The size of the flood area, by quartile, did not modify the risk of HA or ED visits in a monotonic manner.

Finally, on the community level, stratification was performed on the quartile of composite SVI to explore potential effect modification by community social vulnerability factors. There was no consistent trend across increasing SVI quartile and all confidence intervals overlapped.

Cost Analysis

Three methods were used to estimate costs and compare them between the flood hazard and control periods, with results shown in Table 8. The beneficiary-level analysis comparing hazard and control period costs with a paired t-test found an increased cost of \$17 per exposed beneficiary (95%CI: \$15.15 - \$18.84). The ZCTA-level analysis employing a conditional fixed-effects linear regression found mean ZCTA-level costs to be \$27,908 greater in the hazard period compared to control (95%CI: \$24,662 - \$31,194). Finally, the third method incorporating the AR% results and average cost per visit type found a national cost estimate of \$14,672,577 (95%CI: \$13,151,211 – \$16,054,473) for ED visits and \$246,776,147 (95%CI: \$224,576,584 – \$267,986,807) for hospitalizations, using the mean cost per visit of \$690 per ED visit and \$14,700 per hospitalization as previously cited from AHRQ, for the ten-year study period.^{29,30}

Discussion

Summary of key findings

This study provides insight into the impact of flood exposure on healthcare utilization and costs among older adults in the United States, a field of study with a substantial knowledge gap. Utilizing a decade of data, we observed a notable increase in healthcare encounters, specifically ED visits and HA, following flood exposure for a range of conditions. These findings underscore the substantial health impact of large-scale floods on vulnerable populations.

Our cohort, comprising over 11.8 million Medicare beneficiaries aged 65 and older, reflects a fraction of the older adult population at risk during flood events, but does reflect a population with a disproportionate vulnerability due to age and underlying comorbid health conditions. The demographic diversity within this cohort provides some basis for understanding flood-related health impacts across various racial subgroups, although this cohort was disproportionately White compared to the overall US population during the same period.³¹

The ITSA revealed a statistically significant increase in the population-level risk of ED visits following flood exposure for all-cause, GI-specific, and mental health visits. The ED visit model predictions increased immediately after flood onset; while the model predictions were not statistically significant for hospitalizations, the model predictions demonstrated trends towards increased utilization up to 8 weeks after flood onset. The findings of the ITSA were used to inform the ZCTA-level analysis design of Analysis 2. *A priori*, the control and hazard period length was 4-weeks in duration and this was supported by the ITSA. We considered using shorter periods, however had concerns about lag times to diagnosis, particularly for mental health conditions and those requiring hospitalization. While considering longer periods greater than 4-weeks, we had concerns about residual confounding and longer secular and seasonal trends and therefore limited the control and hazard periods to 4-weeks in the subsequent ZCTA-level cohort analysis.

The ZCTA-level analysis of all-cause and cause-specific diagnoses demonstrated flood-related increases in IRR for all-cause and nearly all diagnosis-specific visits, with the highest increases in visit rates among metabolic and renal conditions, infectious diseases, injuries, cardiovascular

and respiratory conditions. The attributable risk percentages of these visits ranged from 3.1 to 10.5% of visits, with substantial nationwide excess attributable visits on the order of thousands of visits and a greater volume of ED visits compared to hospitalizations. Mental health diagnoses were the one category not statistically significant for ED visits, although they were for hospitalizations.

The ZCTA-level stratified analysis among the cohort of exposed Medicare beneficiaries further illuminated the differential impact of floods across various individual-level and flood-specific factors. Sex-stratification revealed higher IRR associated with males compared to females with overlapping confidence intervals, but consistent with prior literature on sex-specific mortality of flood exposure, although prior literature has demonstrated higher morbidity among females and flood exposure.^{2,11} Age-stratification demonstrated statistically significant increases in IRR among increasing age categories, and suggested effect modification by age category consistent with prior literature.¹¹ There were sample size limitations for the race-stratified analysis, which compared only White and Black-identified beneficiaries, without statistically significant differences. With respect to flood-specific factors, there did appear to be seasonal differences in IRR with healthcare utilization rates in the summer substantially higher than the spring, with overlapping confidence intervals with the other seasons but no significant difference in flood geographic extent. Finally, when stratified by quartile of composite SVI, no significant difference was observed.

The economic analysis revealed a substantial increase in healthcare costs associated with flood exposure, at the individual, ZCTA, and nationwide levels.

Contextualizing the Results in the Existing Literature

Our findings address the gaps in the existing literature on health impacts of flood exposure, particularly with respect to the impacts on an array of health conditions explored, over a broad geographic area exposed, and extensive study period.

Prior investigations of flood-related health impacts have focused on mortality assessments, which we did not include in this analysis, as well as a select number of diagnosis-specific outcomes. A series of studies in Massachusetts evaluated healthcare utilization for GI illness and found flood exposure associated with increased risk of GI visits of a similar magnitude odds ratio (1.08) to what we observed in our analysis.¹⁸

Another common flood investigation approach has focused on tropical storm-associated floods. On such analysis of ED visits after Tropical Storm Imelda in 2019 in Texas using syndromic surveillance data observed increased rate ratios of healthcare encounters for diarrhea (1.15), dehydration (1.07), asthma (1.06), and cardiovascular (1.05) complaints of a slightly higher magnitude than in our analysis.³² Similarly, in this stratified analysis, there was no overall difference in sex-stratified results, nor results by White or Black racial category stratification, however our analysis did find age-group differences while theirs did not, albeit with wider confidence intervals and smaller population size. Another storm-related flood analysis among ED visits in New York City from Hurricane Sandy in 2012 found increased relative risk of ED visits for cardiovascular (1.10), respiratory (1.35), skin and soft tissue infection (1.20), injuries (1.19), and renal-related diagnoses (1.44) among adults 65 years and above, primarily in the first week after flood exposure, with substantially lower effect size magnitudes that were not statistically significant after the first week.³³ The magnitude of these associations are more robust than those found in our analysis, which may have been related to their analytic approach of stratification by week, whereas in our analysis the entire four-week period after flood onset

was considered together, potentially diluting the effect of exposure. Notably, they also found the greatest magnitude of an association with renal diagnoses, suggesting those patients with underlying renal disease or end-stage renal disease on dialysis may experience substantial impacts on receiving routine dialysis maintenance therapy in the setting of flood exposure, placing them at great risk of subsequent complications from missing dialysis. Similarly, the other condition-specific results may suggest increased risk of health impacts among those with pre-existing diabetes, cardiovascular or respiratory disease given the association with healthcare utilization for skin and soft tissue infections, cardiovascular and respiratory conditions.

Limited economic assessments of flood exposure have been performed in the US and the prior focus has been primarily on property damage assessments rather than health impacts and associated healthcare costs. One analysis of six climate change-related hazards estimated the costs associated with the Red River flood in North Dakota in 2009, including costs of premature death (\$15.8 million), hospitalization (\$839,000), and ED visits (\$232,000) calculated from health outcomes of 2 premature deaths, 43 excess hospitalizations, and 263 additional ED visits among an estimated 139,918 exposed people.⁶ The three costs analyses we performed were on different geographical scales, resulting in a broad range of costs; our ZCTA-level findings of mean excess costs of \$27,908 per ZCTA is a lower magnitude than reported in this Red River assessment. This may suggest our findings are an underestimate as their cost estimates were higher and incorporated all payers not just Medicare, however they do not report the number of ZCTA exposed to the Red River Flood, therefore directly comparing these costs has limitations.

Strengths

One of the key strengths in our study lies in the use of a large database of Medicare beneficiaries, including a range of clinical outcomes over a large geographical and temporal extent in the CONUS. Linking this database with a comprehensive database of large floods resulted in an analysis of healthcare outcomes and costs on a scale in the US not previously published to our knowledge. Utilizing a cohort of Medicare beneficiaries in the four weeks before and after floods allowed us to conduct stratified analyses on individual level factors to limit confounding and evaluate for effect modification.

Limitations

This analysis is not without limitations. The exposure dataset is limited to floods exceeding the 20-year return period and does not permit for a more refined estimation of flood intensity, apart from duration and geographical extent. It is, however, the most extensive geographic and geospatial open-access flood dataset we have encountered after extensive search and evaluation of other datasets. The methods in this analysis also rely on an ecological design, as we do not know about individual-level exposure to the floods, apart from their occurrence within the ZCTA in which the Medicare beneficiary lived. The structure of the cohort analysis, with healthcare data availability limited to the 4-week period before and after flood start, may have introduced bias due to conditioning on the presence of a flood during this period; as a result, there is no truly unexposed population in this analysis and this design may present residual bias and time-invariant confounding we could not control for.

From the standpoint of healthcare utilization, the Medicare dataset inherently limits the analysis to adults 65 years and older based on program eligibility, excluding younger adults and children apart from rare exceptions, which were excluded due to low sample size and unique diagnoses, as discussed above. From prior investigations, however, older adults are a demographic group

that experiences a high vulnerability to health impacts of flood exposure.^{2,11} In addition, while we hypothesized that the health impacts resulting from the flood exposure occurred within the 4-week period after flood onset, we may not have fully captured the delayed health effects. Furthermore, mortality data was not included in this analysis as out-of-hospital mortality was not available in our dataset, which limits our results and conclusions to an analysis of morbidity alone. Finally, the healthcare cost estimations used claims data as reported in the Medicare dataset, which may not fully capture the total healthcare costs resulting from flood exposure. The calculations in the cost analysis generalizing to the national level relied on national estimates of the average cost of ED visits and HA to Medicare, which inherently limit the analysis in their use of a single numerical estimation.

Future investigations

While this analysis provides insights on a broader scale geographically and temporally than prior efforts, the findings highlight opportunities to improve upon the work in future efforts. These could include an evaluation of a broader population in ages, including children and adults under 65 years, that make up a greater share of the national population. Flood exposure in this analysis was considered based on home address within a ZCTA that experienced flooding, but a more refined geospatial assessment could be performed to identify those with particularly close proximity to flooded areas. With respect to the temporal exposure assessment, in this analysis we considered outcomes in the 4 weeks before and after flood start, which could be more refined to evaluate week-over-week or daily exposure and outcomes, which may provide a more nuanced picture of health impacts, particularly considering differences in the physiological responses to floods, disruptions in healthcare, and evacuations. Finally, the social vulnerability assessment in this analysis was limited to the composite SVI on the county level; subsequent investigations could consider other individual-level factors or other specific metrics that contribute to the composite SVI that may play a more direct role in predicting community or individual vulnerability to flood exposure.

Conclusions

Our study presents compelling evidence of the significant impact of large-scale flood events on healthcare utilization and associated costs among older adults in the United States. The increased rates of ED visits and HA following floods, particularly among vulnerable groups such as the oldest adults, emphasize the need for targeted public health interventions and enhanced disaster preparedness strategies. The substantial economic burden observed in the wake of such environmental disasters underscores the vast societal costs of unmitigated anthropogenic climate change. Furthermore, it highlights that cost estimates of disasters that do not account for human morbidity and mortality are substantial underestimates. While our findings contribute valuable insights to the understanding of flood-related health impacts, they also highlight the necessity for ongoing research in this area, especially in the context of an aging population and a changing climate. Future studies should aim to incorporate more detailed environmental and individual-level data to further refine our understanding of the complex interplay between flood events and public health.

Tables and Figures

Table 1 – 2015 Clinical Classifications Software (CCS) level 3 codes used for the identification of cause-specific outcomes for interrupted time series analysis (ITSA) (Analysis 1).

<i>Category</i>	<i>CCS Code</i>	<i>Diagnosis</i>
Mental health (MH)	650	Adjustment disorders
	651	Anxiety disorders
	657	Mood disorders
	659	Schizophrenia and psychotic disorders
	660	Alcohol-related disorders
	661	Substance-related disorders
	662	Suicide and intentional self-injury
Gastrointestinal (GI)	135	Intestinal infection
	144	Enteritis and colitis
	154	Non-infectious gastroenteritis

Table 2 – 2015 Clinical Classifications Software (CCS) level 3 codes used for the identification of cause-specific outcomes for ZIP code tabulation area (ZCTA)-level cohort analysis (Analysis 2).

<i>Category</i>	<i>CCS Codes</i>
Infectious and parasitic diseases (ID)	1-10, 76-78, 90, 92, 122-126, 135, 144, 148, 159, 197, 201
Metabolic, electrolytes, and renal (FEN)	48-52, 55, 58, 156-157
Cardiovascular and cerebrovascular (CV)	96-113, 116-118, 245
Respiratory (Resp)	122-134
Gastrointestinal (GI)	135, 139-140, 142, 144-146, 148-149, 151-155, 250-251
Orthopedic, external injury and poisoning (INJ)	225-244, 2601-2621
Mental health (MH)	650-651, 657-663, 670

Table 3 – Frequency of ZIP code tabulation area (ZCTA) floods and median duration in the study period from the Multi-sourced Flood Inventories (MFI) by month and year.

<i>Month</i>	<i>Jan</i>	<i>Feb</i>	<i>Mar</i>	<i>Apr</i>	<i>May</i>	<i>Jun</i>	<i>Jul</i>	<i>Aug</i>	<i>Sep</i>	<i>Oct</i>	<i>Nov</i>	<i>Dec</i>
ZCTA Floods	476	180	1699	1694	3628	2436	362	1536	1813	920	112	1680
Median Duration (days)	3	22	16	5	40	29	4	9	8	9	9	10
<i>Year</i>	<i>2008</i>	<i>2009</i>	<i>2010</i>	<i>2011</i>	<i>2012</i>	<i>2013</i>	<i>2014</i>	<i>2015</i>	<i>2016</i>	<i>2017</i>		
ZCTA Floods	2051	942	1837	3033	309	975	875	3108	1442	1964		
Median Duration (days)	20	7	5	33	11	8	35	11	12	7		

Table 4 – Medicare beneficiary cohort baseline demographic characteristics and flood exposure. SD is standard deviation.

<i>Characteristics</i>	<i>Medicare Beneficiaries (%)</i>
Unique beneficiaries	11,801,527 (100)
<i>Age</i>	
Age in years, mean (SD)	74.4 (SD 7.6)
<i>Sex</i>	
Male	5,156,174 (43.7)
Female	6,645,353 (56.3)
<i>Race</i>	
White	10,422,915 (88.3)
Black	884,380 (7.5)
Asian	101,190 (0.9)
Hispanic	139,734 (1.2)
American Indian or Alaskan Native	56,147 (0.5)
Other	113,179 (1.0)
Unknown	83,982 (0.7)
<i>Flood exposure</i>	
Floods per beneficiary, mean (SD)	1.3 (SD 0.6)

Table 5 – Interrupted time series analysis (ITSA) regression all-cause and cause-specific relative risk (RR) and 95% confidence interval (CI) results by week and visit type (Analysis 1), comparing pre- and post-flood period.

<i>ITSA Duration</i>	<i>Encounter Type</i>	<i>RR</i>	<i>Lower 95% CI</i>	<i>Upper 95% CI</i>
2-weeks	ED - All-Cause	1.037	1.026	1.049
	ED - GI	1.120	1.009	1.245
	ED - MH	1.075	1.003	1.153
	HA - All-Cause	1.018	0.993	1.043
	HA - GI	0.982	0.799	1.211
	HA - MH	1.024	0.895	1.172
4-weeks	ED - All-Cause	1.017	1.010	1.024
	ED - GI	1.091	1.025	1.162
	ED - MH	1.029	0.987	1.073
	HA - All-Cause	1.006	0.991	1.020
	HA - GI	0.947	0.836	1.074
	HA - MH	1.045	0.965	1.132
6-weeks	ED - All-Cause	1.011	1.005	1.016
	ED - GI	1.071	1.020	1.126
	ED - MH	1.024	0.990	1.058
	HA - All-Cause	1.000	0.989	1.012
	HA - GI	1.027	0.929	1.135
	HA - MH	1.027	0.964	1.094
8-weeks	ED - All-Cause	1.013	1.009	1.018
	ED - GI	1.065	1.021	1.112
	ED - MH	1.034	1.005	1.064
	HA - All-Cause	1.002	0.992	1.012
	HA - GI	1.062	0.974	1.157
	HA - MH	1.011	0.958	1.068

Table 6 – ZIP code tabulation area (ZCTA)-level regression analysis all-cause and cause-specific resulting incident rate ratio (IRR) and 95% confidence intervals (CI) by visit type and attributable risk percentage (AR%) and estimated attributable excess visits (Analysis 2), comparing pre- and post-flood period.

<i>Encounter Type</i>	<i>Diagnosis Type</i>	<i>IRR</i>	<i>Lower 95% CI</i>	<i>Upper 95% CI</i>	<i>AR%</i>	<i>Visits in Flood Period</i>	<i>Excess Attributable Visits</i>
ED	All-Cause	1.048	1.043	1.053	4.6%	462,274	21,265
	Cardiovascular	1.05	1.041	1.06	4.8%	93,697	4,497
	Metabolic, renal	1.084	1.062	1.106	7.7%	20,840	1,605
	Gastrointestinal	1.032	1.018	1.045	3.1%	46,884	1,453
	Infectious disease	1.07	1.058	1.083	6.5%	67,077	4,360
	Respiratory	1.037	1.023	1.05	3.6%	57,908	2,085
	Injury	1.051	1.039	1.062	4.8%	76,392	3,667
	Mental health	1.034	0.99	1.07	-	-	-
	Inpatient	All-Cause	1.074	1.067	1.081	6.9%	243,297
Cardiovascular		1.068	1.056	1.081	6.4%	59,614	3,815
Metabolic, renal		1.095	1.068	1.122	8.7%	14,101	1,227
Gastrointestinal		1.043	1.023	1.064	4.1%	21,206	869
Infectious disease		1.117	1.101	1.133	10.5%	41,674	4,376
Respiratory		1.091	1.072	1.108	8.3%	31,309	2,599
Injury		1.081	1.055	1.107	7.5%	15,690	1,177
Mental health		1.085	1.034	1.137	7.8%	3,641	284

Table 7 – ZIP code tabulation area (ZCTA)-level regression stratified analysis all-cause incident rate ratio (IRR) and 95% confidence intervals (CI) by visit type and attributable risk percentage (AR%) and estimated attributable excess visits (Analysis 2), comparing pre- and post-flood period.

<i>Encounter Type</i>	<i>Diagnosis Type</i>	<i>IRR</i>	<i>Lower 95% CI</i>	<i>Upper 95% CI</i>	<i>AR%</i>	<i>Visits in Flood Period</i>	<i>Excess Attributable Visits</i>
Sex-stratified							
Male	ED	1.052	1.045	1.059	5.0%	190,121	9,506
	HA	1.084	1.074	1.093	7.7%	106,703	8,216
Female	ED	1.046	1.039	1.051	4.4%	272,153	11,975
	HA	1.066	1.058	1.075	6.2%	136,594	8,469
Age-stratified							
65-74	ED	1.03	1.023	1.037	2.9%	193,252	5,604
	HA	1.049	1.039	1.059	4.7%	99,060	4,656
75-84	ED	1.046	1.038	1.054	4.4%	166,206	7,313
	HA	1.073	1.063	1.084	6.8%	90,461	6,151
85+	ED	1.089	1.079	1.099	8.1%	102,816	8,328
	HA	1.124	1.11	1.138	11.0%	53,776	5,915
Race-stratified							
White	ED	1.047	1.042	1.052	4.50%	399,640	17,984
	HA	1.074	1.067	1.081	6.80%	214,567	14,591
Black	ED	1.054	1.039	1.068	5.10%	46,851	2,389
	HA	1.084	1.061	1.106	7.70%	20,984	1,616
Season-stratified							
Winter	ED	1.033	1.02	1.045	3.2%	64,338	2,059
	HA	1.061	1.045	1.078	5.8%	34,288	1,989
Spring	ED	1.039	1.032	1.046	3.8%	175,027	6,651
	HA	1.048	1.038	1.058	4.6%	92,562	4,258
Summer	ED	1.067	1.056	1.077	6.2%	122,470	7,593
	HA	1.111	1.097	1.126	10.0%	65,201	6,520
Fall	ED	1.049	1.038	1.06	4.7%	100,439	4,721
	HA	1.085	1.071	1.099	7.8%	51,246	3,997
Flood area-stratified							
Quartile 1	ED	1.049	1.039	1.058	4.6%	130,759	6,015
	HA	1.076	1.064	1.088	7.1%	69,697	4,948
Quartile 2	ED	1.065	1.056	1.074	6.1%	139,959	8,537
	HA	1.084	1.07	1.098	7.7%	67,665	5,210
Quartile 3	ED	1.035	1.025	1.044	3.3%	100,174	3,306
	HA	1.068	1.054	1.081	6.4%	54,328	3,477
Quartile 4	ED	1.037	1.027	1.047	3.6%	91,382	3,290
	HA	1.063	1.05	1.076	5.9%	51,607	3,045
SVI quartile-stratified							
Quartile 1	ED	1.041	1.031	1.052	3.9%	85,750	3,344
	HA	1.078	1.062	1.093	7.2%	45,743	3,293
Quartile 2	ED	1.044	1.035	1.054	4.2%	121,893	5,120
	HA	1.075	1.063	1.087	7.0%	64,730	4,531
Quartile 3	ED	1.054	1.044	1.063	5.1%	130,317	6,646
	HA	1.077	1.063	1.09	7.1%	68,668	4,875
Quartile 4	ED	1.048	1.038	1.058	4.6%	124,314	5,718
	HA	1.066	1.053	1.079	6.2%	64,156	3,978

Table 8 – Cost of Medicare claims associated with post-flood period compared to pre-flood period. Cost analysis results by analysis type, including results from excess visit calculation from attributable risk percentage based upon Analysis 2. All costs have been adjusted to 2017 USD. Excess visit and cost per visit results shown only for the third cost analysis and cost per visit estimates were sourced from the Agency for Healthcare Research and Quality (AHRQ) as cited in the manuscript.

<i>Cost analysis type</i>	<i>Excess visits (95% CI)</i>	<i>Cost per visit (\$)</i>	<i>Mean cost (\$) and 95% CI</i>
Beneficiary-level			17.00 (15.15, 18.84)
ZCTA-level			27,908 (24,662, 31,194)
Excess flood-attributed ED visits	21,265 (19,508, 23,627)	690	14,672,577 (13,150,211, 16,054,473)
Excess flood-attributed hospitalizations	16,787 (15,277, 18,230)	14,700	246,776,147 (224,576,584, 267,986,807)

Figure 1 – Map of the total number of ZIP code tabulation area (ZCTA)-floods in the continental US (CONUS) over the study period 2008-2017, by ZCTA.

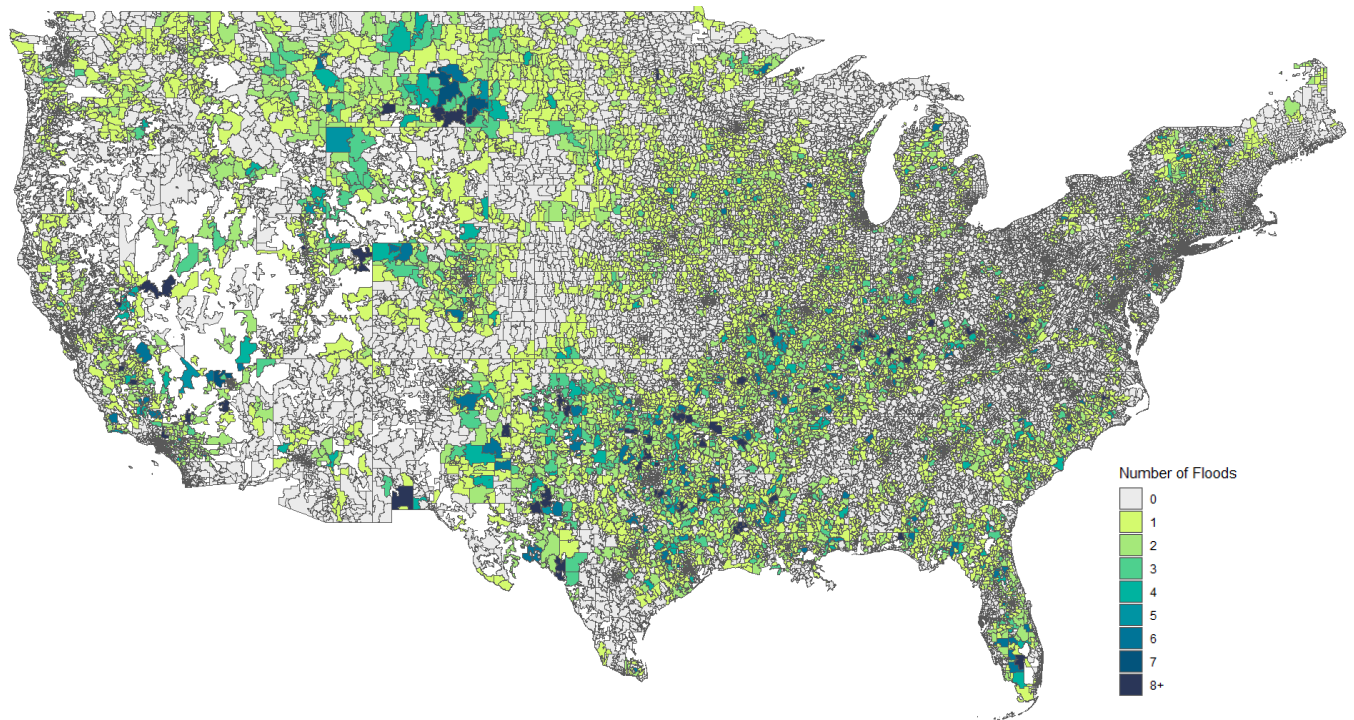


Figure 2 – Map of the quintile of the total duration of ZIP code tabulation area (ZCTA)-floods in the continental US (CONUS) in days over the study period 2008-2017, by ZCTA.

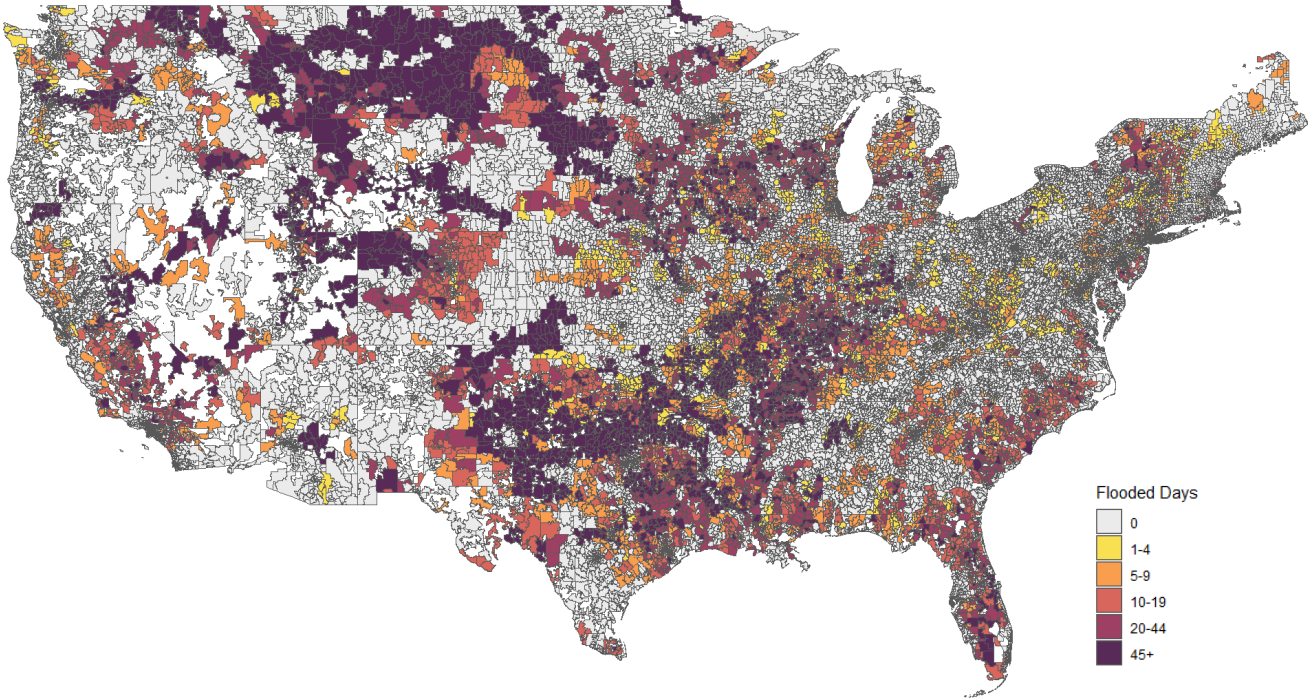


Figure 3 – Interrupted time series analysis (ITSA) for select diagnoses in the 8-week period before and after flood start (Analysis 1). Observed weekly diagnosis counts are shown in red, with ITSA model-predicted values in blue with 95% confidence intervals in grey.

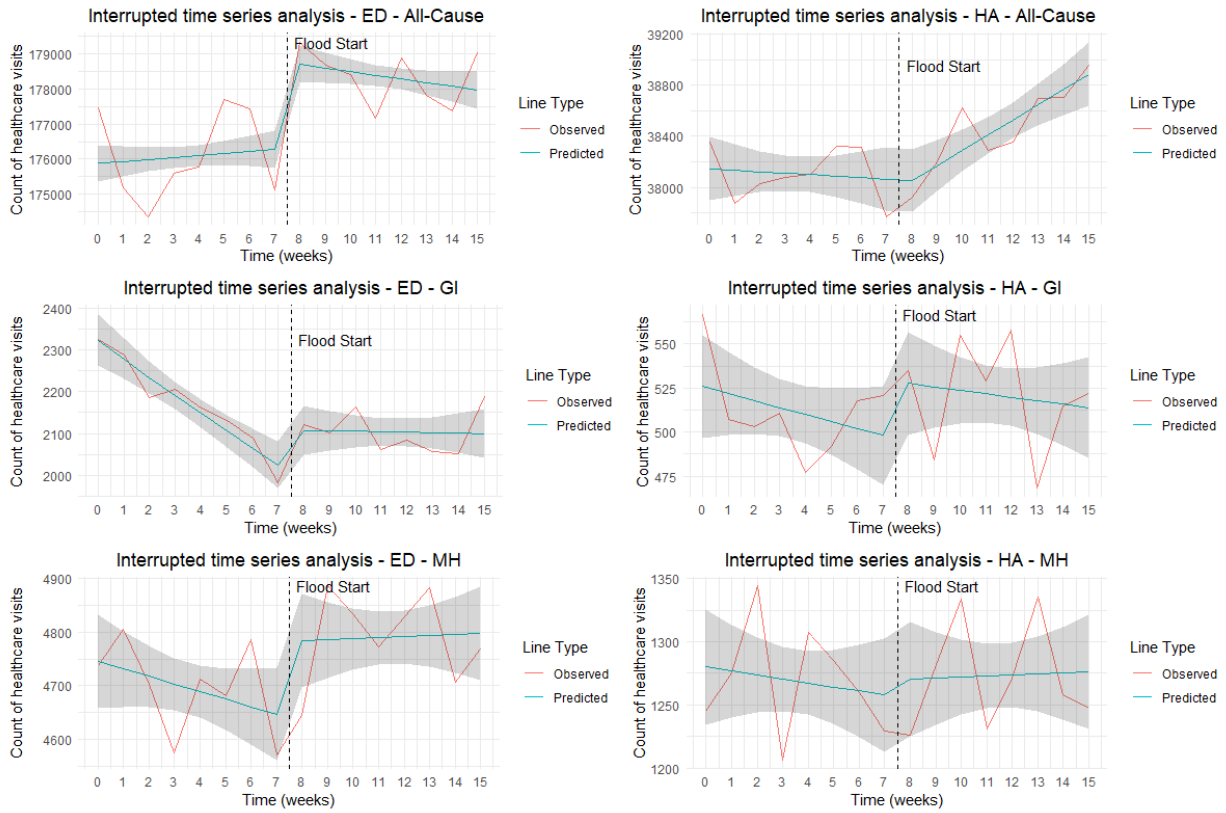


Figure 4 – ZIP code tabulation area (ZCTA)-level stratified regression analysis results showing the incident rate ratio (IRR) and corresponding 95% confidence intervals, by visit type and stratified analysis (Analysis 2), comparing pre- and post-flood period.



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