Specific Aims. In past decades, the United States has experienced a rise in sea-level and the frequency of heavy downpours,[1,2] posing growing challenges to the life and health of coastal residents. The health, social and economic impacts of common, recurring Atlantic tropical and winter coastal storms may continue to worsen through higher surge intensity and wider land flooding. These impacts can be particularly severe in densely populated urban coastal areas where accumulating infrastructure damages can have the most dramatic effect. Moreover, marine sediments, stirred up by storms and carried to land by flooding, are polluted with a plethora of persistent organic (e.g. pesticides) and inorganic compounds (e.g. heavy metals),[3,4] increasing potentially the hazardous exposure of coastal residents. A related concern is storm water-related sewage and wastewater overflow which can spread pathogens and dump toxic chemicals into coastal waters.[5,6] Without appropriate research and evidence-based responses, the storm- and flood-related health risks of coastal residents are expected to grow.[7]

These risks become increasingly evident when hurricanes—tropical storms in their most extreme form—reach the coast, e.g. Katrina in New Orleans (2005), Sandy in New York City (2012) and the highly destructive 2017-2018 Atlantic Hurricane seasons (Harvey, Irma, Maria, Florence and Michael). The consequences of these hurricanes are devastating for the economy,[8–10] environment,[11,12] and human health.[7,13,14] A recent report by the National Centers for Environmental Information estimated that storm-related costs in the US between 1980 and 2017 exceeded $1.3 trillion.[15] Studies have shown different aspects of the severe acute health consequences of hurricanes, including mortality and physical injuries,[13,14,16] reportable disease,[17,18] gastrointestinal (GI) and respiratory illnesses,[19,20] and mental health.[21–24] However, little if any research is being devoted to understanding and quantifying the health impacts of frequent year-round minor coastal flooding events over time.

The cumulative economic cost of frequent minor coastal flooding events is projected to exceed the costs of the extreme but infrequent hurricane events for which cities typically prepare.[25] **We hypothesize that multiple moderate coastal storms, which hit the Atlantic coast and Gulf of Mexico year-round,[26–29] will have cumulative negative health consequences exceeding those of relatively rare hurricanes.**

To address this significant knowledge gap, we will leverage the dynamic cohort of Medicare in the 18 Atlantic Ocean and Gulf of Mexico states (>13 million enrollees per year) to obtain information about all emergency department (ED) visits in these states (1999 – 2016) and couple these health data with publicly available information on dates and characteristics of hurricanes, coastal storms and flood events. **To best prepare for these emergencies, our goal is to develop a new evidence-based approach to comprehensively quantify health risks for several ED outcomes associated with coastal storms and flood events and to identify the most vulnerable subpopulations.** Our study **aims** are to:

1. **Determine the acute impact of all coastal storms and flood events** on total ED visits, as well as respiratory-, GI-, and injury-related ED visits (i.e. same day and within a week).
   - **a.** Assess effect modification by storm characteristics, e.g. precipitation, wind speed, storm type (e.g. hurricanes, tropical storms and depressions, Nor'easters, etc.), intensity, and duration.
   - **b.** Assess whether other extreme weather conditions before the storm amplify storm impacts on ED visit profiles, such as heat or cold waves.
   - **c.** Investigate the increases in ED visits for anxiety and panic disorder events during the week preceding extreme events specifically, i.e. hurricanes.
2. **Identify vulnerable subpopulations and communities** by characterizing the potential heterogeneity of coastal storm impacts on ED visits across levels of community-level socioeconomic status and living conditions, such as metrics of deprivation and housing quality. Characterizing heterogeneity is critical, as (a) storm-related impacts may only be observed in vulnerable communities and (b) identification of community-level drivers of vulnerability can inform the development of targeted storm preparedness strategies.
3. **Identify the complete spectrum of all storm-related causes for ED visits**, beyond the *a priori* hypothesized respiratory, GI and injury-related visits, using information on all reported ED visit codes, **to comprehensively quantify the acute health impact of coastal storms**.

Impact: Our findings will provide critical novel insights for (1) understanding how recurring coastal storms and flood events acutely impact human health; (2) identifying particularly vulnerable subpopulations and communities; and (3) developing sustainable storm preparedness strategies—beyond just the extreme events—aimed for increasingly frequent year-round coastal storm events. Importantly, this two-year project will be key to moving the field forward; we plan in future work to investigate the cumulative health effects of these recurring coastal storms, and extend geographically (e.g. West Coast) and to other populations (e.g. Medicaid).

A. Significance

A1. Climate Change Impact on Oceans and Coastal Storms

In the past fifty years, in association with accelerated anthropogenic pollution, temperatures globally have significantly increased, causing ice melt and thermal expansion of the ocean.[30] The combination of these two phenomena has produced a problematic rise in sea-level (~1.6 mm/year) threatening multiple coastal areas worldwide, especially those which already had a high sea elevation relative to land.[29] Moreover, the frequency of heavy (>50.8 mm/day) and very heavy (>101.6 mm/day) downpours has been reported to be multiplied by a factor of 2-3 across the United States, with the Northeast at the higher end of the range.[1,2] Altogether, these climate-related changes are predicted to worsen the impact of recurring coastal storms by producing higher surge intensity and wider land flooding. Besides, even if the incidence of regular coastal storms did not show any clear modification with climate change, the frequency of major storms is undoubtedly on the rise.[31] It has been forecast that coastal cities can expect a nine-fold increase in flooding by 2050.[32] In addition, the recurrence interval of major devastating storm surge in the Northeast could become every 30 to 70 years by 2050 (every 8 to 30 years in low-lying cities).[29] This will pose growing challenges to the life and health of residents of coastal areas, which are more densely populated than the hinterland and exhibit higher rates of population growth and urbanization.[33] For instance, the population in coastal US areas has increased by 39% from 1970 to 2010,[34] a trend which is not expected to reverse, as long as coastal urban centers continue to concentrate economic and social activity.[35]

We propose to *comprehensively* assess the impact of coastal storm events on acute health outcomes, how these are modified by storm characteristics, other concurrent extreme weather events, and neighborhood deprivation.

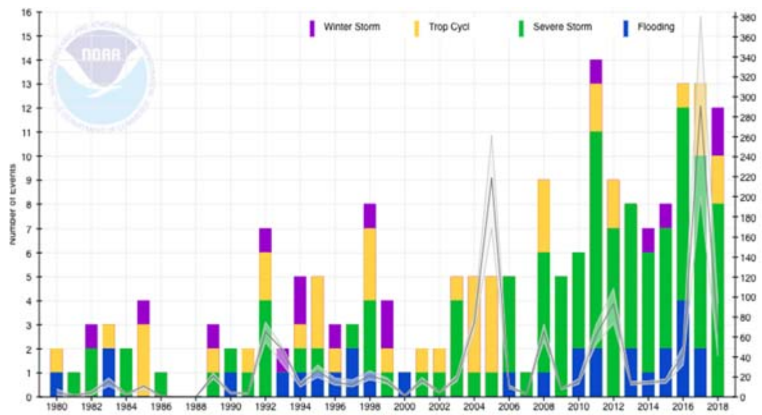

Figure 1. *Consumer Price Index (CPI)-adjusted billion-dollar disaster event types by year (NOAA 2019): Winter storms (purple), tropical cyclones (yellow), severe storms (green), and flooding events (blue). The gray line represents annual costs (in billion dollars).*

A2. Impacts on Human Health

The impact of coastal storms and flood events has not been widely explored, with the exception of few notable hurricanes, like Sandy in New York City (NYC; 2012) and Katrina in New Orleans, LA (2005). The health consequences of coastal floods are multiple and variable, and depend on a number of factors, including the particular context of the storm event. For instance, if coastal flooding happens during the summer months, warm temperatures will favor the development of communicable diseases.[36]

Specifically, Hurricane Katrina has been linked to increased risk for myocardial infarction (MI) that persisted even after 3 and 6 years,[37,38] post-traumatic stress disorder (PTSD),[22] especially among pregnant women,[23,24] fetal mortality and distress,[39,40] and adult mortality,[41] among others. Similarly, several studies have been published since Sandy passed over NYC and they have reported increased risk for mortality and physical injuries,[16] reportable disease,[18] gastrointestinal and respiratory illnesses,[20] and mental health.[21] Moreover, although not widely studied, it has been suggested that it is likely that certain outcomes, such as anxiety and panic attacks, are more frequent preceding a large storm.[42]

Although the impacts of the devastating recent extreme storm events (Hurricanes Harvey, Maria and Irma in 2017, and Florence and Michael in 2018) have not yet been investigated in depth, a recent small sample size study found that 46% of the study participants met the threshold for probable PTSD following Hurricane Harvey's landfall.[43] Moreover, when Hurricane Harvey made landfall over Galveston Bay and the Houston Ship Chanel, TX, concerns grew about the threat of toxic exposures from the more than 500 industrial sites in the area and the potential health consequences to the more than 6.5 million residents of the Houston area.[44]

Even though, to our knowledge, winter storms and Nor'easters have not been specifically investigated in relationship to adverse health, severe winter weather has been associated with carbon monoxide poisoning,[45–47] preterm births,[48] and storm-related injuries.[49] Additionally, cold waves—in general—have been linked to mortality,[50] and increased snowfall to cold-related emergency department (ED) visits, ED visits for injuries, and delayed cardiovascular events.[51]

No study to date, to our knowledge, has **comprehensively assessed the impact of coastal storms**, both tropical and winter storms, as well as more frequent minor storms, on human health. We propose to address this important knowledge gap with the proposed study, incorporating information on all storms—with varying intensity—that passed over the Atlantic coast and Gulf of Mexico, between 1999 and 2016. Furthermore, we will also investigate whether the observed effects are modified by coastal storm characteristics, such as intensity, precipitation, snowfall, etc.

A2a. The role of neighborhood-level socioeconomic status on the health impacts of coastal storms

Impacts of extreme weather events, such as hurricanes, can be devastating on residents in affected areas. And even though extreme events do not select which communities to impact based on the characteristics of the communities, it has been repeatedly shown that such characteristics play a very important role on risk communication, help during evacuation, existing infrastructure and housing characteristics relevant to protection, and resilience.[52,53] It has been shown that residents in low-income communities tend to be differentially impacted (physically and psychologically), and that disaster impacts differ by socioeconomic status (SES) during all periods around the disaster: emergency response, recovery, and reconstruction.[54] Even adjusting for characteristics of the built and natural environment, socially vulnerable communities have been found to experience significantly higher rates of casualties.[55] Gee et al.[56] present a stress-exposure-disease conceptual framework under which psychosocial stress is a key contributor to differential vulnerability. When environmental stressors cannot be ameliorated by community resources, they can lead directly to health disparities and amplify the adverse impacts of the environmental exposures.[56]

Socioeconomic factors played a very important role, for instance, on whom Hurricane Katrina mostly affected. According to a Congressional Research Service (CRS) Report for Congress,[57] "the storm impacted heavily on the poor and African Americans. CRS estimates that one-fifth of those displaced by the storm were likely to have been poor, and 30% had incomes that were below 1½ times the poverty line. African Americans are estimated to have accounted for approximately 44% of the storm victims."

A limited number of studies have attempted to quantify the role of neighborhood SES on storm and flood impacts; however, these focus on very restricted areas (e.g. one city or three coastal communities in MS) or single extreme events.[58–60] To our knowledge, to date, no study has **comprehensively** evaluated the role neighborhood SES plays in both extreme and more frequent storm and flood events.

Identifying sensitive populations that may be less likely to respond to, cope with and recover from a natural disaster, based on social vulnerability, has significant implications for **social and environmental equity**, and is especially important as it will greatly **improve emergency management** and **the design and development of community-based emergency plans**.[61] To our knowledge, social vulnerability to more frequent and less intense events has not yet been investigated. This is a critical knowledge gap, as the impacts of such events might disproportionately impact certain populations based on socioeconomic factors.

Contribution of this Research. The contribution of this research will be *significant*, as we will *comprehensively* assess the impact of coastal storm and flood events on human health, using data from a very rich administrative dataset with all emergency department (ED) visits and a detailed and extensive record of all storm and flood events in Atlantic Coast and Gulf of Mexico states during 1999–2016. We will also investigate how coastal storm characteristics, other concurrent extreme events, such as heat waves, modify the observed associations, and identify vulnerable subpopulations and communities to storm and flood events.

B. Innovation

1. This is a highly innovative project as, to the best of our knowledge, it will be the first to **comprehensively** assess the impact of **all coastal storm and flood events on acute** health outcomes, using daily data of all ED visits across the Atlantic coast states.
2. This will also be the first study to evaluate the differential impact of **specific coastal storm types**, such as tropical vs. winter storms, by **storm type**, e.g. Hurricanes vs. Nor'easters, and **storm characteristics,** such as intensity, duration and precipitation.
3. Moreover, we will adopt an approach highly relevant to **environmental justice** issues, by evaluating how coastal storm-related health impacts vary by different community characteristics with a **special emphasis on neighborhood deprivation and segregation**.
4. Our study also uniquely proposes to **identify all possible causes for ED visits during coastal storms and flood events**, beyond the *a priori* hypothesized respiratory, gastrointestinal and injury-related ED visits, thus comprehensively characterizing the acute impacts of storms and flood events on health.

Impact: With this study, we will address a critical knowledge gap: we will comprehensively assess the acute health impacts of recurring coastal storms and flood events, which have been rarely studied, as well as extreme hurricane events. Our results will provide critical insights for understanding how such events impact human health, for identifying particularly vulnerable coastal communities, and for stressing the need of developing sustainable storm preparedness strategies—beyond just the extreme events—aimed for increasingly frequent year-round coastal storm events.

C. Approach

C1. Investigative Team

We have a unique and highly interdisciplinary team participating in this project. **Dr. Kioumourtzoglou** is an environmental engineer and environmental epidemiologist with extensive experience using statistical methods to estimate effects of environmental factors on acute outcomes. **Dr. Dominici** is an international leader in the development and application of statistical and epidemiological methods. **Dr. Zanobetti** is an environmental epidemiologist with extensive experience in characterizing weather-related health impacts, and in identifying vulnerable subgroups to environmental insults. **Dr. Re** is a biologist and toxicologist with expertise in exposure to pesticides, heavy metals and mold. **Dr. Hernández** is a sociologist focusing on environmental justice issues. **Dr. Shaman's** background is in climate, atmospheric science and hydrology, and his research focuses on the nexus on climate and health, studying a number of climatic phenomena, including storms.

C2. Preliminary Results

We conducted a preliminary analysis to demonstrate feasibility and investigate the association between summer tropical coastal storms and increased respiratory emergency department (ED) visits in New York (NY) state (1995 – 2015). County-specific counts for ED visits were obtained from the NY Department of Health Statewide Planning and Research Cooperative System (SPARCS), and exposure data on summer tropical storms were obtained from hurricane tracking charts available at National Oceanic and Atmospheric Administration's (NOAA) National Hurricane Center website.[62] Tropical storms that passed within 1 degree of NY state counties were assigned as exposures. We observed that the day of the storm, the rate of respiratory ED visits increased by 9.97% (95%CI: 0.93 – 19.81%). The effect estimates were highest in NYC and Long Island, which experienced 14.8% and 17.0% increases in the rate of respiratory ED visits, respectively.

C3. Data proposed for use

C3a. Study Population

We will leverage a nationally representative open cohort from CMS:[63] all Fee-for-Service (FFS) Medicare enrollees $\geq$65 years old (1999–2016), the largest US health insurance provider. Medicare includes demographic information, such as age, sex, race, residential zipcode, and date of death. We will use Medicare data on ED visits for the proposed work for the following states along the Atlantic Coast and Gulf of Mexico: ME, NH, MA, RI, CT, NY, PA, DE, MD, VA, NC, SC, GA, FL, AL, MS, LA, TX, and DC (>13 million enrollees per year).

C3b. Outcome Definitions

In Medicare, disease diagnoses are established using the International Classification of Diseases, 9th Revision Clinical Modification (ICD-9; Center for Disease Control and Prevention 2008). We will use information on all ED visits during 1999 – 2016 in the study area (~ 3.8 million per year), as well as on all respiratory- (codes 460-519), gastrointestinal (GI; codes 530-579) and injury-related (codes 800-995) ED visits. We will also use information on anxiety- and panic-related ED visits (codes 300.0, 300.1, 300.2, 308). For Aim 3, to identify all possible causes of hospitalization due to coastal storms and flood events, we will use information on all 15,072 possible ICD-9 codes. We will categorize these codes into 283 mutually exclusive, clinically meaningful disease categories using the validated Clinical Classifications Software (CCS) algorithm developed by the Agency for Healthcare Research and Quality.[64] We will remove all pregnancy- and fertility-related disease groups, as these are rarely observed among the older population.

C3c. Exposure Assessment

We will obtain data on coastal storm events, including tropical storms and Nor'easters, as well as flood and flash flood events, from NOAA's National Center for Environmental Information Storm Events Database,[65] NOAA's National Hurricane Center[62] (see e.g. **Figure 2**) and the Northeast Regional Climate Center.[66] We will also obtain information on the Regional Snowfall Index (RSI),[67] and on other weather variables, including temperature, pressure, precipitation,

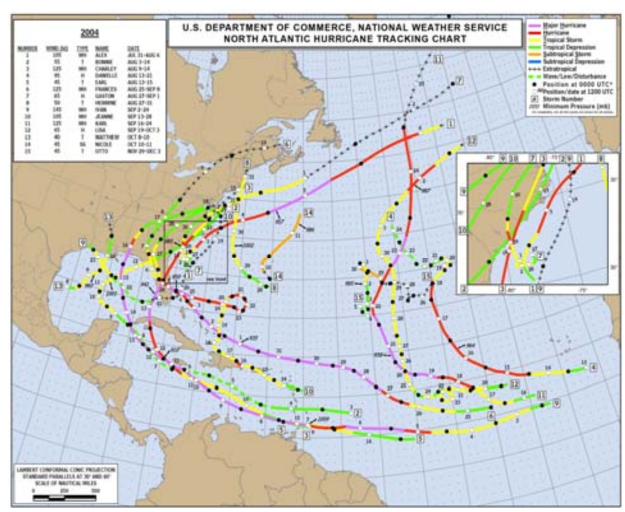

Figure 2. Hurricane Tracks in the North Atlantic (2004).

wind speed and direction, and relative humidity from the National Climatic Data Center.[68] We will use the Federal Emergency Management Agency's National Flood Risk Reports to identify flood hazard areas.[69] We will assign exposure to each zipcode based on whether a storm passed within 100 km of the zipcode centroid. We will assess the robustness of our results evaluating the choice of 100 km by assessing also storms passing within 20 to 500 km from each zipcode centroid.

C3d. Community-level Variables

We will use data from the 2000 and 2010 Census[70] and the American Community Surveys (ACS)[71] after 2005 to obtain information on zipcodes and characterize the community-level socio-economic status (SES). Specifically, we will use information on the zipcode-specific population density (per square mile), proportion of the population over 65 years old, median household income, proportion in poverty, proportion of families in poverty, proportion of Hispanic/Latino, white, black and Asian residents, proportion of residents with and without high-school degrees and with a college degree. County-level annual unemployment rates will be obtained from the US Bureau of Labor Statistics.[72] Information on housing characteristics within zipcode will also be obtained from the Census and the ACS, as well as the American Housing Survey.[73] These variables represent contextual factors of neighborhood environment, such as housing, residential stability, poverty, employment, occupation, racial composition, and education. We will also assess racial residential segregation (a measure of how the neighborhood racial/ethnic composition deviates from the surrounding city's racial/ethnic composition).[74,75]

C4. Statistical Analysis

Data analyses will begin with application of traditional exploratory techniques; univariate analyses will be performed for all variables. Outlying values will be assessed and checked for validity. With these analyses, the study characteristics will be described. Skewed variables that need transformation will be identified. We will assess effect modification by **biologically relevant variables** by stratifying the health models described below (Section **C4a**) by levels of sex and age.

C4a. Determine the acute impact of storms on ED visits (<u>Aim 1</u>)

We will create zipcode-specific daily counts of the outcomes of interest (total number of ED visits, as well as respiratory-, GI- and injury-related ED visits; also see **C3b**). We will subsequently run time series analyses, employing generalized linear mixed models (GLMM), to estimate the change in the rate of these outcomes during coastal storms (as a binary daily variable at first), using zipcode specific random intercepts to account for within zipcode clustering. We will use a quasi-Poisson likelihood estimation, thus allowing for any potential over-dispersion in the outcomes. To adjust for temporal confounding by long-term and seasonal trends we will include natural splines and select the optimal number of degrees of freedom per year using the Akaike's Information Criterion (AIC). We will nonlinearly adjust for temperature and relative humidity using natural splines. To adjust for spatial confounding across zipcodes, we will include in the model zipcode-specific variables (Section **C3d**). We will also evaluate the association with the duration of the storms, by using as the exposure the number of storm days during the previous ten days instead of the binary variable described above. Since all hospitalizations in the Medicare population during the study period are available, we will conduct sensitivity analyses by only including the first hospitalization, and evaluate the role of length of hospitalization stay in the associations of interest.

To assess lagged exposures, we will fit distributed lag nonlinear models (DLNM);[51,76–79] we will consider lags in a week and include indicator variables in the model simultaneously indicating presence of a storm for each lag day in the week. The DLNM framework allows adjustment for exposures at other days while estimating the temporal trends of this association, assuming that it varies smoothly as a function of time.[76–79] From this model we will also be able to obtain the rate ratio for the total number of ED visits in the weeklong period after a storm day, i.e. cumulative effect, over the total number of ED visits in the weeklong period after a no-storm day. In addition, we will also fit a DLNM for 30 lag days, to assess sub-chronic effects up to a month post-storm.

Finally, we will restrict our analyses for Aim 1 to the Hurricane season (June to November each year) to specifically evaluate Hurricane events, and repeat analyses as described above, using a binary daily variable for Hurricanes. To adjust for secular trends in this model we will include tensor product smooths of the calendar year and days within each Hurricane season, i.e. we will allow thus the parameterization of the smooth function to vary by Hurricane season.

C4b. Effect modification by storm characteristics (<u>Aim 1a</u>)

We will assess whether the observed storm-related effect estimates are modified by storm characteristics, by including interaction terms in the above-described models (Section **C4a**). We will explore the following storm characteristics: duration, intensity, central pressure and pressure gradient, precipitation, snowfall and RSI, wind speed and direction, storm type (e.g. hurricanes, tropical storms and depressions, Nor'easters, etc.), temperature, and relative humidity. Information on certain storm characteristics, such as precipitation and temperature, is available for the entire duration of the study periods and not only during storm days; these will be included in the model for all days and the main effects of these during non-storm days will also be estimated. We will test the assumption of linearity in the main effects of the continuous storm characteristics using penalized splines. If nonlinear associations are detected, we will then estimate whether the shape of the exposure-response curve is modified by storm vs. non-storm days. If power allows, instead of using interaction terms, we will stratify analyses and look separately at different events (e.g. Nor'easter winter storms vs. hurricanes and tropical storms vs. other smaller flooding events).

Because many of these characteristics are expected to be correlated during different coastal storm categories, we will also create a storm index, by employing k-means clustering, an algorithm that seeks to partition M points (in our analysis the number of storm days) in N dimensions (the number of storm characteristics) into k clusters (storm index).[80,81] We will then use this newly derived storm index in the above-described model to assess whether this index modifies the association between coastal storm events and ED visits.

C4c. Do other extreme weather conditions before the storm amplify storm impacts? (Aim 1b)

We will assess whether presence of other extreme weather events, the frequency and intensity of which is likely to also be impacted by climate change, namely heat and cold waves, modifies the association between coastal storms and ED visits. Although no consistent definition exists for temperature waves, we define cold waves as at least two consecutive days with daily temperature lower than the 5th percentile of temperatures in each location during the study period,[50] and, similarly, heat waves as least two consecutive days with daily temperature higher than the 99th percentile of temperatures.[82] Sensitivity analyses will be conducted to assess the robustness of our results to the choice of the number of days in the wave definitions by also investigating at least three- and at least four-day waves. For this analysis, we will include in our main model an interaction term between wave days and storm events, including all other potential confounders in the model.

C4d. Investigate the increases in anxiety ED visits during the week preceding a hurricane (Aim 1c)

To evaluate potential changes in the ED visit rates for anxiety and panic disorders the week preceding hurricane landfall, we will employ an interrupted time series design.[83] Specifically, we will use a model to represent the phase during which the change (here news of imminent hurricane landfall at a certain location) is being gradually introduced and may (1) change the slope of the association, before (2) leading to a temporary level change following its introduction (at landfall and following days), and (3) eventually gradually return to initial or in any case stable levels.[83] We will adjust for temporal and spatial confounding as described in Section **C4a**. This design is appropriate for abrupt or gradual "interventions" (here the news) and immediate or lagged effects.[83,84] We will conduct sensitivity analyses on the choice of the week interval prior to hurricane landfall by evaluating different potential timings of news breaking, from ~10 days up to a few days prior to the event.

C4e. Effect modification by community-level socioeconomic status and living conditions (Aim 2)

To identify vulnerable subpopulations and neighborhoods, we will assess whether the estimated effects vary across communities. First, we will run a GLMM with random intercepts, as described in Section **C4a**, additionally including random slopes for zipcodes. We will then test whether significant heterogeneity is present in the effect estimates across zipcodes, i.e. whether the variability of the estimated random effects across zip-codes indicates presence of heterogeneity. We will subsequently explore whether zipcode-specific SES characteristics contribute to this heterogeneity, using the variables listed in Section **C3d**, by including interaction terms between zipcode-specific characteristics and storm events in the above-described model (Section **C4a**).

However, all these zipcode-level variables are expected to be highly correlated. We will therefore repeat analyses by combining information across these variables by estimating a neighborhood deprivation index (NDI),[85] and assess whether NDI modifies the association between coastal storms and ED visits. This method has been extensively used to characterize neighborhood deprivation in health studies.[86–89] Briefly, we will conduct principal components analysis (PCA) and retain the variables with the higher loadings on the first component that explain the majority of the variability in the data. We will then repeat PCA and use the final loadings for the included variables on the first component to calculate a deprivation summary score, i.e. NDI, for each zipcode. The NDI will then be considered as a continuous variable.

Furthermore, we will apply a novel method for *de novo* discovery of vulnerable subgroups.[90] Briefly, this method leverages tree-based algorithms for *de novo* discovery of subgroups coupled with a highly efficient randomization-based hypothesis testing for quantifying the strength of evidence of heterogeneity of the storm effects across the identified subgroups. This method can incorporate information on both continuous and categorical effect modifiers and accommodate higher order and non-linear interactions, thus providing the best possible evidence on vulnerable subgroups.

C4f. Identify all possible causes for hospital admissions and ED visits (Aim 3)

To comprehensively assess the acute impacts of coastal storms and flooding events on health it is important to investigate the association with multiple outcomes and not only the *a priori* hypothesized causes. Therefore, we will repeat the analyses described in Section **C4a**, using counts for each of the CCS disease categories as the outcome of interest (see Section **C3b**). We will use Bonferroni-corrected p-values to adjust for multiple comparisons. Furthermore, we will repeat analyses in a hierarchical Bayesian framework, thus allowing borrowing of information across similarly impacted categories within disease groups.

C5. Power Calculations

Because no direct method exists to calculate power from time series models, we followed a simulation protocol and ran 200 simulations. For our simulations we (1) used the state-wide daily counts of Medicare total, respiratory, GI- and injury-related ED visits for each state, based on the average daily numbers across the study period, and (2) assumed on average 5-20 storm days per year. For the proposed study duration, our estimated power is shown in Figure 3. The lowest observed power was estimated for respiratory-related ED visits: we calculated power of 80% to estimate a 5% increase in respiratory ED visits if only 5 storm days per year are observed. To assess power to detect effect modification, we used respiratory-related ED visits, as for these we calculated the lowest power to detect main effects, and we assumed a dichotomized at the median potential modifier. We calculated power of 85% and 98% for a 50% increase in the effect estimate for 5 and 10 storm days per year, respectively. Please note that these are conservative power calculations for effect modification, as almost no modifiers in our study are binary; we have therefore likely severely underestimated our power to detect significant effect modification by variables with multiple categories (e.g. storm category) and continuous variables (such as concurrent weather conditions and neighborhood deprivation). Overall, we are confident that we have sufficient power to conduct the proposed work.

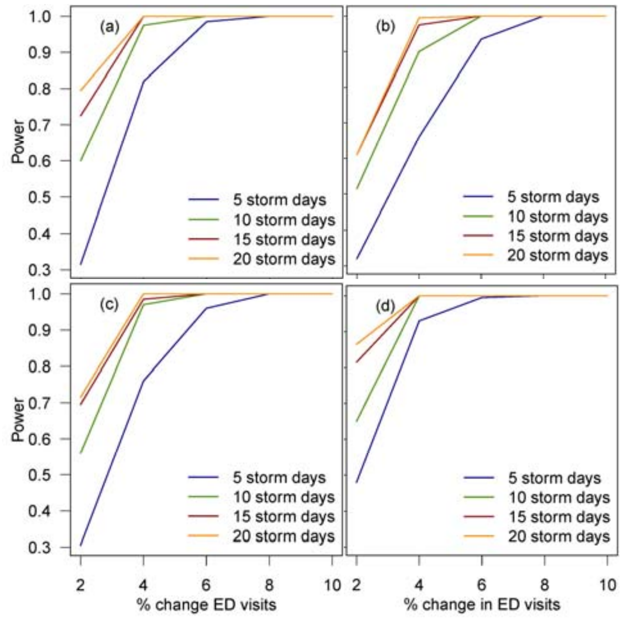

Figure 3. Estimated power for (a) total, (b) respiratory, (c) GI, and (d) injury-related ED visits.

C6. Limitations and Alternative Approaches

Generalizability. For this study we will leverage data from Medicare enrollees residing in 18 states across the Atlantic coast. Medicare enrollees, however, are eligible for Medicare only after becoming 65 years of age. Therefore, our results may not be generalizable to Americans of all ages. Nonetheless, this will be the first study to comprehensively evaluate the health impacts of coastal storm and flood events, in an already vulnerable subpopulation, the elderly.

Statistical power for zipcode-specific analyses. When assessing effect modification by neighborhood deprivation we proposed to conduct analyses at the zipcode level. Although unlikely, it is possible to observe very low or no day-to-day variability in the number of ED visits—or very low or zero ED visits—in some of these zipcodes, potentially impacting model fit. If we observe this, we will conduct analyses aggregating daily counts at the county level to increase numbers of observations per unit.

C7. Timeline and Organization

The study team will have monthly meetings to discuss progress, project relevant issues, data analyses, results, interpretation of study findings and planning of the dissemination activities.

	Y1-Q1	*Y1-Q2*	*Y1-Q3*	*Y1-Q4*	*Y2-Q1*	*Y2-Q2*	*Y2-Q3*	*Y2-Q4*
Data collection & clean up								
Aim 1								
Aim 2								
Aim 3								
Presentation/manuscript preparation and submission								

References

1. Groisman PY, Knight RW, Karl TR, Groisman PY, Knight RW, Karl TR. Heavy Precipitation and High Streamflow in the Contiguous United States: Trends in the Twentieth Century. *Bull Am Meteorol Soc*. 2001;82(2):219-246. doi:10.1175/1520-0477(2001)082<0219:HPAHSI>2.3.CO;2.

2. Sallenger AH, Doran KS, Howd PA. Hotspot of accelerated sea-level rise on the Atlantic coast of North America. *Nat Clim Chang*. 2012;2(12):884-888. doi:10.1038/nclimate1597.

3. Euripidou E, Murray V. Public health impacts of floods and chemical contamination. *J Public Health (Bangkok)*. 2004;26(4):376-383. doi:10.1093/pubmed/fdh163.

4. Mandigo AC, DiScenza DJ, Keimowitz AR, Fitzgerald N. Chemical contamination of soils in the New York City area following Hurricane Sandy. *Environ Geochem Health*. 2016;38(5):1115-1124. doi:10.1007/s10653-015-9776-y.

5. Kondo MC, Low SC, Henning J, Branas CC. The impact of green stormwater infrastructure installation on surrounding health and safety. *Am J Public Health*. 2015;105(3):e114-e121. doi:10.2105/AJPH.2014.302314.

6. Kenward A, Yawitz D, Raja U. *Sewage Overflows from Hurrican Sandy*. Princeton, NJ https://www.climatecentral.org/pdfs/Sewage.pdf.

7. Lane K, Charles-Guzman K, Wheeler K, Abid Z, Graber N, Matte T. Health effects of coastal storms and flooding in urban areas: a review and vulnerability assessment. *J Environ Public Health*. 2013;2013:913064. doi:10.1155/2013/913064.

8. One City, Rebuilding Together–Progress Update.

9. Burton M, Hicks M. Hurricane Katrina: Preliminary estimates of commercial and public sector damages. *Marshall Univ Cent Bus Econ Res*. 2005;(September):1-13. http://marshall.edu/cber/research/katrina/Katrina-Estimates.pdf.

10. Pielke RA, Landsea CW. Normalized Hurricane Damages in the United States: 1925–95. *Weather Forecast*. 1998;13(3):621-631. doi:10.1175/1520-0434(1998)013<0621:NHDITU>2.0.CO;2.

11. Manuel J. The long road to recovery: environmental health impacts of Hurricane Sandy. *Environ Health Perspect*. 2013;121(5):a152-9. doi:10.1289/ehp.121-a152.

12. Pardue JH, Moe WM, McInnis D, et al. Chemical and microbiological parameters in New Orleans floodwater following hurricane Katrina. *Environ Sci Technol*. 2005;39(22):8591-8599. doi:10.1021/es0518631.

13. August O, Katrina H. Mortality associated with Hurricane Katrina--Florida and Alabama, August-October 2005. *MMWR Morb Mortal Wkly Rep*. 2006;55(9):239-242. doi:10.2307/23316424.

14. Brunkard J, Namulanda G, Ratard R. Hurricane katrina deaths, Louisiana, 2005. *Disaster Med Public Health Prep*. 2008;2(4):215-223. doi:10.1097/DMP.0b013e31818aaf55.

15. NOAA. *National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters*.; 2018. https://www.ncdc.noaa.gov/billions/.

16. Seil K, Spira-Cohen A, Marcum J. Injury Deaths Related to Hurricane Sandy, New York City, 2012. *Disaster Med Public Health Prep*. 2016;10(03):378-385. doi:10.1017/dmp.2016.36.

17. CDC. *Surveillance in Hurricane Evacuation Centers--Louisiana, September-October 2005.* Vol 55. 2006. doi:mm5502a3 [pii].

18. Greene SK, Wilson EL, Konty KJ, Fine AD. Assessment of reportable disease incidence after Hurricane Sandy, New York City, 2012. *Disaster Med Public Health Prep*. 2013;7(5):513-521. doi:10.1017/dmp.2013.98.

19. Edwards TD, Young RA, Lowe AF. Caring for a surge of hurricane katrina evacuees in primary care clinics. *Ann Fam Med*. 2007;5(2):170-174. doi:10.1370/afm.646.

20. Sebek K, Jacobson L, Wang J, Newton-Dame R, Singer J. Assessing Capacity and Disease Burden in a Virtual Network of New York City Primary Care Providers Following Hurricane Sandy. *J Urban Heal*.

2014;91(4):615-622. doi:10.1007/s11524-014-9874-7.

21. Neria Y, Shultz JM. Mental health effects of Hurricane Sandy: characteristics, potential aftermath, and response. *JAMA*. 2012;308(24):2571-2572. doi:10.1001/jama.2012.110700.

22. DeSalvo KB, Hyre AD, Ompad DC, Menke A, Tynes LL, Muntner P. Symptoms of posttraumatic stress disorder in a New Orleans workforce following Hurricane Katrina. *J Urban Heal*. 2007;84(2):142-152. doi:10.1007/s11524-006-9147-1.

23. Tees MT, Harville EW, Xiong X, Buekens P, Pridjian G, Elkind-Hirsch K. Hurricane Katrina-related maternal stress, maternal mental health, and Early Infant Temperament. *Matern Child Health J*. 2010;14(4):511-518. doi:10.1007/s10995-009-0486-x.

24. Xiong X, Harville EW, Mattison DR, Elkind-Hirsch K, Pridjian G, Buekens P. Hurricane Katrina experience and the risk of post-traumatic stress disorder and depression among pregnant women. *Am J Disaster Med*. 2010;5(3):181-187. doi:10.1097/MAJ.0b013e318180f21c.

25. Moftakhari HR, AghaKouchak A, Sanders BF, Matthew RA. Cumulative hazard: The case of nuisance flooding. *Earth's Futur*. January 2017. doi:10.1002/2016EF000494.

26. Woodruff JD, Irish JL, Camargo SJ. Coastal flooding by tropical cyclones and sea-level rise. *Nature*. 2013;504(7478):44-52. doi:10.1038/nature12855.

27. Nicholls RJ. Coastal flooding and wetland loss in the 21st century: Changes under the SRES climate and socio-economic scenarios. *Glob Environ Chang*. 2004;14(1):69-86. doi:10.1016/j.gloenvcha.2003.10.007.

28. Colle BA, Rojowsky K, Buonaito F, Colle BA, Rojowsky K, Buonaito F. New York City Storm Surges: Climatology and an Analysis of the Wind and Cyclone Evolution. *J Appl Meteorol Climatol*. 2010;49(1):85-100. doi:10.1175/2009JAMC2189.1.

29. Kirshen P, Watson C, Douglas E, Gontz A, Lee J, Tian Y. Coastal flooding in the Northeastern United States due to climate change. *Mitig Adapt Strateg Glob Chang*. 2008;13(5-6):437-451. doi:10.1007/s11027-007-9130-5.

30. Solomon S, Intergovernmental Panel on Climate Change., Intergovernmental Panel on Climate Change. Working Group I. *Climate Change 2007 : The Physical Science Basis : Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press; 2007.

31. Keim BD, Muller RA, Stone GW. Spatial and temporal variability of coastal storms in the North Atlantic Basin. *Mar Geol*. 2004;210(1):7-15. doi:10.1016/j.margeo.2003.12.006.

32. Hallegatte S. Strategies to adapt to an uncertain climate change. *Glob Environ Chang*. 2009;19(2):240-247. doi:10.1016/j.gloenvcha.2008.12.003.

33. Neumann B, Vafeidis AT, Zimmermann J, Nicholls RJ. Future Coastal Population Growth and Exposure to Sea-Level Rise and Coastal Flooding - A Global Assessment. Kumar L, ed. *PLoS One*. 2015;10(3):e0118571. doi:10.1371/journal.pone.0118571.

34. Thomas J. Culliton. *Population: Distribution, Density and Growth*. Silver Spring, MD; 1998.

35. Wilson GW, Fischetti TR. Coastline Population Trends in the United States : 1960 to 2008. *U S Cencus Bur*. 2010;(P25-1139):1-28.

36. Huang L-Y, Wang Y-C, Wu C-C, Chen Y-C, Huang Y-L. Risk of Flood-Related Diseases of Eyes, Skin and Gastrointestinal Tract in Taiwan: A Retrospective Cohort Study. Shaman J, ed. *PLoS One*. 2016;11(5):e0155166. doi:10.1371/journal.pone.0155166.

37. Jiao Z, Kakoulides S V., Moscona J, et al. Effect of Hurricane Katrina on incidence of acute myocardial infarction in New Orleans three years after the storm. *Am J Cardiol*. 2012;109(4):502-505. doi:10.1016/j.amjcard.2011.09.045.

38. Peters MN, Moscona JC, Katz MJ, et al. Natural disasters and myocardial infarction: The six years after hurricane katrina. *Mayo Clin Proc*. 2014;89(4):472-477. doi:10.1016/j.mayocp.2013.12.013.

39. Zahran S, Snodgrass JG, Peek L, Weiler S. Maternal Hurricane Exposure and Fetal Distress Risk. *Risk Anal*. 2010;30(10):1590-1601. doi:10.1111/j.1539-6924.2010.01453.x.

40. Zahran I. M.; Link, B. G.; Snodgrass, J. G.; Weiler, S.; Mielke, H. W. S. B. Maternal exposure to hurricane destruction and fetal mortality. *J Epidemiol Community Heal*. 2014;68(8):760-766. doi:http://dx.doi.org/10.1136/jech-2014-203807.

41. August O, Katrina H. Mortality associated with Hurricane Katrina--Florida and Alabama, August-October 2005. *MMWR Morb Mortal Wkly Rep*. 2006;55(9):239-242. doi:10.2307/23316424.

42. Bulbena A, Pailhez G, Aceña R, et al. Panic anxiety, under the weather? *Int J Biometeorol*. 2005;49(4):238-243. doi:10.1007/s00484-004-0236-0.

43. Schwartz R, Tuminello S, Kerath S, Rios J, Lieberman-Cribbin W, Taioli E. Preliminary Assessment of Hurricane Harvey Exposures and Mental Health Impact. *Int J Env Res Public Heal*. 2018;15(5).

44. Friedrich MJ. Determining health effects of hazardous materials released during hurricane harvey. *JAMA - J Am Med Assoc*. 2017;318(23):2283-2285. doi:10.1001/jama.2017.15558.

45. Chen BC, Shawn LK, Connors NJ, et al. Carbon monoxide exposures in New York City following Hurricane Sandy in 2012. *Clin Toxicol*. 2013;51(9):879-885. doi:10.3109/15563650.2013.839030.

46. Centers for Disease Control and Prevention (CDC). Unintentional carbon monoxide poisoning following a winter storm--Washington, January 1993. *MMWR Morb Mortal Wkly Rep*. 1993;42(6):109-111. doi:10.1001/jama.1993.03500110036016.

47. Houck PM, Hampson NB. Epidemic carbon monoxide poisoning following a winter storm. *J Emerg Med*. 1997;15(4):469-473. doi:10.1016/S0736-4679(97)00079-6.

48. N. A, E. K, M. G, M. D. Preterm birth during an extreme weather event in Quebec, Canada: a “natural experiment.” *Matern Child Health J*. 2011;15(7):1088-1096. doi:10.1007/s10995-010-0645-0.

49. Piercefield E, Wendling T, Archer P, Mallonee S. Winter storm-related injuries in Oklahoma, January 2007. *J Safety Res*. 2011;42(1):27-32. doi:10.1016/j.jsr.2010.11.004.

50. Wang Y, Shi L, Zanobetti A, Schwartz JD. Estimating and projecting the effect of cold waves on mortality in 209 US cities. *Environ Int*. 2016;94:141-149. doi:10.1016/j.envint.2016.05.008.

51. Bobb JF, Ho KKL, Yeh RW, et al. Original Contribution Time-Course of Cause-Speci fi c Hospital Admissions During Snowstorms : An Analysis of Electronic Medical Records From Major Hospitals in Boston , Massachusetts. 2017;185(10):283-294. doi:10.1093/aje/kww219.

52. Lindell M, Prater CS. Assessing Community Impacts of Natural Disasters. *Nat Hazards Rev*. 2003;4(4):176-185.

53. Kahn M. THE DEATH TOLL FROM NATURAL DISASTERS: THE ROLE OF INCOME, GEOGRAPHY, AND INSTITUTIONS. *Rev Econ Stat*. 2005;87(2):271-284.

54. Fothergill A, Peek L. Poverty and Disasters in the United States: A Review of Recent Sociological Findings. *Nat Hazards*. 2004;32:89-110.

55. Zahran S, Brody S, Gillis Peacock W, Vedlitz A, Grover H. Social vulnerability and the natural and built environment: a model of flood casualties in Texas. *Disasters*. 2008;32(4):537-560.

56. Gee GC, Payne-Sturges DC. Environmental health disparities: A framework integrating psychosocial and environmental concepts. *Environ Health Perspect*. 2004. doi:10.1289/ehp.7074.

57. Gabe T, Falk G, McCarthy M, Mason V. *CRS Report for Congress - Hurricane Katrina: Social-Demographic Characteristics of Impacted Areas*. The Library of Congress; 2005.

58. Lane K, Charles-Guzman K, Wheeler K, Abid Z, Graber N, Matte T. Health effects of coastal storms and flooding in urban areas: A review and vulnerability assessment. *J Environ Public Health*. 2013. doi:10.1155/2013/913064.

59. Bathi JR, Das HS. Vulnerability of coastal communities from storm surge and flood disasters. *Int J Environ Res Public Health*. 2016. doi:10.3390/ijerph13020239.

60. Hernández D, Chang D, Hutchinson C, et al. Public Housing on the Periphery: Vulnerable Residents and Depleted Resilience Reserves post-Hurricane Sandy. *J Urban Heal*. 2018. doi:10.1007/s11524-018-0280-4.

61. Cutter SL, Finch C. Temporal and spatial changes in social vulnerability to natural hazards. *Proc Natl Acad Sci U S A*. 2008;105(7):2301-2306. doi:10.1073/pnas.0710375105.

62. NHC. NOAA's National Hurricane Center. http://www.nhc.noaa.gov/.

63. CMS. Centers for Medicare and Medicaid Services. 2015. http://www.cms.gov/. Accessed July 24, 2015.

64. Elixhauser A, Steiner C, Palmer L. *Clinical Classifications Software for ICD-9-CM*. Rockville, MD; 2014.

65. NOAA. Storm Events Database of the National Oceanic and Atmospheric Administration. https://www.ncdc.noaa.gov/stormevents/.

66. NRCC. Northeast Regional Climate Center. http://www.nrcc.cornell.edu/.

67. RSI. Regional Snowfall Index. https://www.ncdc.noaa.gov/snow-and-ice/rsi/.

68. NCDC. National Climatic Data Center. https://www.ncdc.noaa.gov/.

69. FEMA. Federal Emergency Management Agency's National Flood Risk Reports. https://www.fema.gov/national-flood-hazard-layer-nfhl.

70. US Census Bureau. 2010 Census. http://www.census.gov/.

71. ACS. American Community Surveys. https://www.census.gov/programs-surveys/acs/.

72. US Bureau of Labor Statistics. Unemployment. https://www.bls.gov/data/.

73. AHS. *American Housing Survey*. https://www.census.gov/programs-surveys/ahs.html.

74. White K, Borrell LN. Racial/ethnic residential segregation: Framing the context of health risk and health disparities. *Heal Place*. 2011;17(2):438-448. doi:10.1016/j.healthplace.2010.12.002.

75. Kershaw KN, Osypuk TL, Do DP, De Chavez PJ, Roux AVD. Neighborhood-level racial/ethnic residential segregation and incident cardiovascular disease the multi-ethnic study of atherosclerosis. *Circulation*. 2015;131(2):141-148. doi:10.1161/CIRCULATIONAHA.114.011345.

76. Gasparrini A, Armstrong B, Kenward MG. Distributed lag non-linear models. *Stat Med*. 2010;29(21):2224-2234. doi:10.1002/sim.3940.

77. Gasparrini A, Scheipl F, Armstrong B, Kenward MG. A penalized framework for distributed lag non-linear models. *Biometrics*. 2017;73(3):938-948. doi:10.1111/biom.12645.

78. Gasparrini A. Distributed lag non-linear models in R : the package dlnm. *J Stat Softw*. 2011;43(8):1-20.

79. Gasparrini A. Distributed lag linear and non-linear models for time series data. *14310721250*. 2014:1-12.

80. Jain AK, Murty MN, Flynn PJ. Data clustering: a review. *ACM Comput Surv*. 1999;31(3):264-323. doi:10.1145/331499.331504.

81. John A Hartigan and Manchek A Wong. Algorithm as 136: A k-means clustering algorithm. *J R Stat Soc Ser C (Applied Stat*. 1979;28(1):100-108.

82. Bobb JF, Obemeyer Z, Wang Y, Dominici F. Cause-specific risk of hospital admission related to extreme heat in older adults. *Jof Am Med Assoc*. 2014;312(24):2699-2667. doi:10.1001/jama.2014.15715.

83. Lopez Bernal J, Cummins S, Gasparrini A. Interrupted time series regression for the evaluation of public health interventions: a tutorial. *Int J Epidemiol*. 2016:1-8. doi:10.1093/ije/dyw098.

84. Barr CD, Diez DM, Wang Y, Dominici F, Samet JM. Comprehensive smoking bans and acute myocardial infarction among medicare enrollees in 387 US counties: 1999-2008. *Am J Epidemiol*. 2012. doi:10.1093/aje/kws267.

85. Messer LC, Laraia BA, Kaufman JS, et al. The development of a standardized neighborhood deprivation index. *J Urban Heal*. 2006;83(6):1041-1062.

86. O’Campo P, Burke JG, Culhane Jand Elo IT, et al. Neighborhood deprivation and preterm birth among non-Hispanic Black and White women in eight geographic areas in the United States. *Am J Epidemiol*. 2008;167(2):155-163.

87. Major JM, Doubeni CA, Freedman ND, et al. Neighborhood Socioeconomic Deprivation and Mortality: NIH-AARP Diet and Health Study. *PLoS One*. 2010;5(11). doi:10.1371/journal.pone.0015538.

88. Elo IT, Culhane JF, Kohler I V., et al. Neighbourhood deprivation and small-for-gestational-age term births in the United States. *Paediatr Perinat Epidemiol*. 2009;23(1):87-96. doi:10.1111/j.1365-3016.2008.00991.x.

89. Messer LC, Vinikoor LC, Laraia BA, et al. Socioeconomic domains and associations with preterm birth. *Soc Sci Med*. 2008;67(8):1247-1257. doi:10.1016/j.socscimed.2008.06.009.

90. Lee K, Small D, Dominici F. Discovering Effect Modification and Randomization Inference in Air Pollution Studies. *arXiv2*. 2018;arXiv:1802.