DISSERTATION

ASSESSING COMMUNITY-WIDE HEALTH IMPACTS OF NATURAL DISASTERS: STUDIES OF A SEVERE FLOOD IN BEIJING AND TROPICAL CYCLONES IN THE UNITED STATES

Submitted by

Meilin Yan

Department of Environmental and Radiological Health Sciences

In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Fall 2018

Doctoral Committee:

Advisor: G. Brooke Anderson
Co-Advisor: Jennifer L. Peel

Sheryl Magzamen
Ander Wilson

ABSTRACT

ASSESSING COMMUNITY-WIDE HEALTH IMPACTS OF NATURAL DISASTERS: STUDIES OF A SEVERE FLOOD IN BEIJING AND TROPICAL CYCLONES IN THE UNITED STATES

Death and injury tolls occurring during natural disasters have traditionally been estimated using a disaster surveillance approach, where each death or injury is considered case-by-case to determine if it can be attributed to the disaster. This approach may not always capture the overall community-wide health effects associated with disaster exposure, especially in cases where much of the excess morbidity and mortality result from outcomes common outside of disaster periods (e.g., heart attacks, respiratory problems) rather than well-characterized disaster-related risks that are rarer outside of storm events (e.g., drowning, carbon monoxide poisoning, trauma). The goal of this dissertation is to examine the community-wide impacts of natural disasters on some common health outcomes. To achieve this goal, we assessed the community-wide health risks from exposure to two types of climate-related natural disasters, a severe flood and tropical cyclones, as compared with matched unexposed days in the same community. Our results can provide new evidence on how natural disasters affect human health, contributing to and complementing the large base of existing literature generated using a disaster surveillance approach.

Mortality risk of a severe flood. On July 21–22, 2012, Beijing, China, suffered its heaviest rainfall in 60 years, which caused heavy flooding throughout Beijing. We conducted a matched

analysis comparing mortality rates on the peak flood day and the four following days to similar unexposed days in previous years (2008–2011), controlling for potential confounders, to estimate the relative risks (RRs) of daily mortality among Beijing residents associated with this flood. Compared to the matched unexposed days, mortality rates were substantially higher during the flood period for all-cause, circulatory, and accidental mortality, with the highest risks observed on the peak flood day. No evidence of increased risk of respiratory mortality was observed in this study. We estimated a total of 79 excess deaths among Beijing residents on July 21–22, 2012; by contrast, only 34 deaths were reported among Beijing residents in a study estimating the flood's fatality toll using a traditional surveillance approach. Results were robust to study design and modeling choices. Our results indicate considerable impacts of this flood on public health, and that much of this impact may come from increased risk of non-accidental deaths. To our knowledge, this is the first study analyzing the community-wide changes in mortality rates during the 2012 flood in Beijing, and one of the first to do so for any major flood worldwide. This study offers critical evidence in assessing flood-related health impacts, as urban flooding is expected to become more frequent and severe in China.

Health risk of tropical cyclones. To measure storm exposure, we separately considered five metrics—distance to storm track; cumulative rainfall; maximum sustained wind speed; flooding; and tornadoes. For mortality outcomes, we used community vital records for 78 large eastern United States (U.S.) communities, 1988–2005, to estimate the risks of storm exposure on four mortality outcomes. For emergency hospitalization outcomes, we used Medicare claims for 180 eastern US counties, 1999–2010, to estimate storm-related risks on emergency hospitalizations from cardiovascular and respiratory disease among Medicare beneficiaries. We compared the health outcome rates across the study population (all community residents for the mortality analysis; community Medicare beneficiaries for the hospitalization analysis) on storm-exposed days versus similar unexposed days within each community. For each combination of exposure metric and health outcome, we estimated storm-associated health risks for a window from two days before to seven days after the day of storm's closest approach. For the mortality analysis, 92 Atlantic Basin tropical cyclones were considered based on U.S. landfall or close approach, with 70 communities exposed to at least one storm; for the hospitalization analysis, 74 storms were considered for 175 exposed counties. Under the wind-based exposure metric, we found substantially elevated risk for all mortality outcomes considered compared with matched unexposed days, with risk typically highest on the day of the storm's closest approach. When excluding the ten most severe storm events based on wind exposures, however, we did not observe significantly increased risk for the remaining storm exposures on any mortality outcomes. Among Medicare beneficiaries, the cumulative risks of respiratory hospitalizations were increased under all storm exposure metrics considered, for all storm exposures and across all exposed counties; these risks remained significantly elevated even when the ten most severe storm exposures (based on wind exposure) were excluded. Our findings on community-wide health risks from tropical cyclones add important insights to results from disaster surveillance: first, the impacts of tropical cyclones on non-accidental mortality can, in some cases, be much greater than identified in case-by-case surveillance studies; second, there is strong evidence that risks of Medicare emergency hospital admissions due to non-injury morbidity are elevated during the storm exposure period; and third, intense wind exposure can characterize many of the tropical cyclone exposures with particularly high risk on non-accidental mortality, as well as respiratory hospitalizations in the elderly.

ACKNOWLEDGEMENTS

I owe my accomplishments, in large part, to my advisor Dr. G. Brooke Anderson. Dr. Anderson has helped me in many ways in the past few years. She nurtured my passion for becoming an independent researcher in the field of environmental health; guided me to develop the mindset, knowledge, and competency for conducting rigorous research; supported me in socializing with the intellectual and professional communities in my research fields; offered detailed and extremely helpful feedback on my scholarly writing and communication skills; worked hard with me in finding a job that could allow me to continue pursuing my career goals. Without her patience, encouragement, and support, the dissertation would not have been possible.

I would like to thank my co-advisor Dr. Jennifer L. Peel, as well as the other professors on my committee, Dr. Ander Wilson, and Dr. Sheryl Magzamen. They guided me throughout my doctoral study and provided valuable critiques on my dissertation, which have significantly strengthened this work in various ways and at different stages.

I also would like to express my sincere gratitude to Dr. Tiantian Li who works at the Chinese Center for Disease Control and Prevention (CDC). Dr. Li was my co-advisor during my master's study at Peking University in China. Dr. Li guided me into the field of environmental health, offered rich resources for me to explore my research interests, and provided helpful advice on my academic career.

My family deserves my greatest and most heartfelt thanks. My husband Wei Liao gives me love, encouragement, and support on my way to pursuing my doctoral degree. Wei is always optimistic and passionate. He is my superhero whenever I feel depressed and helpless. I am also deeply grateful for the unconditional love and support from my parents, Fuyi Yan and Xiaoping

Feng, and my parents-in-law, Tingzhi Liao and Qimei Hu. In the past few years, they have traveled from China to the United States several times to help Wei and me in welcoming our son to the world and taking good care of him. I owe special love and gratitude to my son Jeremy. He will be four years old when I become Dr. Yan. Jeremy always cheers me up and gives my efforts and life special meanings. He teaches me that adults should always be curious and enthusiastic about the world just as how a child is, though I have to admit that sometimes parenting seems to be even harder than earning a doctoral degree.

My dissertation could not have been completed without my collaborations with Dr. Roger D. Peng from John Hopkins Bloomberg School of Public Health; Dr. Mohammad Z. Al-Hamdan and Dr. William L. Crosson from Universities Space Research Association, NASA; Dr. Andrea Schumacher from Cooperative Institute for Research in the Atmosphere at CSU; Dr. Seth Guikema from the University of Michigan; Dr. Francesca Dominici and Dr. Yun Wang from Harvard T.H. Chan School of Public Health; and Qinghua Sun from China CDC. I also would like to thank everyone in the Colorado State University Department of Environmental and Radiological Health Sciences whom I have worked with and benefited from much in the past few years.

Last but not least, I am grateful for the research grant (grant number: R00ES022631) from the National Institute of Environmental Health Sciences. Without such financial support, I would not have been able to complete this study.

TABLE OF CONTENTS

Chapter 1: Introduction

1. Natural disasters

1.1 Introduction

This dissertation investigates how specific disasters—a severe flood in Beijing and tropical cyclones in the United States—are associated with changes in the community-wide risks of several broad health outcomes. According to the Centre for Research on the Epidemiology of Disasters (CRED), there are six categories of natural disasters: biological (e.g., epidemics), geophysical (e.g., earthquakes), meteorological (e.g., tropical cyclones (TCs)), hydrological (e.g., floods), climatological (e.g., heat waves and wild fires) and extra-terrestrial (e.g., meteorites) (1). Since the late 1990s, many types of meteorological, hydrological, and climatological natural disasters have increased in frequency and intensity, including floods and TCs (2), the two types of disasters investigated in this research.

Floods can occur in inland areas, including drainage floods, river floods, and flash floods, as well as in coastal areas, where floods are often caused by storm surge from tropical cyclones (3). Floods can be caused by or worsened by both climate- and human-related factors (4,5). With changes in climate and land use, the frequency of river, coastal, and flash floods have increased in past years (2), with Asia and Africa more frequently threatened by floods than other continents (2,5). From 1980 to 2009, although the annual frequency of floods has increased around the world, the reported average number of deaths per flooding event (based on disaster surveillance systems) has slightly decreased (5). China, in particular, is one of the countries most frequently impacted by floods. In the past decades, China has experienced several severe floods, including the 1998 Yangtze River flood (> 1,000 deaths) (6), the 1996 Yellow River flood, the 2012 north China flood (7,8) and the 2016 Guangdong flood (9).

TCs are atmospheric circulations that develop over tropical or subtropical oceans and that, after developing, are primarily driven by the heat and moisture from oceans (10–12). TCs are typically characterized by a number of hazards that can affect humans, including storm surges, strong winds (which usually weaken rapidly after the storm's landfall), and heavy precipitation (10–12). Worldwide, TCs can originate over six tropical and subtropical ocean basins: North Atlantic, Northeast Pacific, Northwest Pacific, North Indian Ocean, South Indian Ocean, and Southwest Pacific-Australia (13,14). Thus, countries and regions bordering these TC basins typically most affected by TCs; these include Australia, South China, Japan, the Korean Peninsula, the Philippines, and the eastern United States. Depending on where it develops among these basins and its intensity, a TC is referred to by different names. For example, TCs that develop in the northwestern Pacific Ocean basin are called typhoons, while those that develop in the Atlantic basin and northeastern Pacific Ocean and have maximum sustained wind speed exceeding 33 m/s are called hurricanes (10). In the Atlantic basin, the Saffir-Simpson scale (with Category 1 to 5 ratings) is commonly used to characterize a hurricane based on the sustained wind speed, as well as to roughly estimate the potential damage of storm (15). In the Atlantic basin, the TC season generally lasts from June to November, typically peaking in September (16). While the timing of tropical cyclone seasons are almost the same over other basins in the northern hemisphere, in the southern hemisphere—South Indian and Southwest Pacific-Australia basin—the TC season generally runs from November to April (17). TC formation can be influenced by a number of slower-varying patterns in the climate system, including seas surface temperature, as well as by different oscillation patterns including the El Nino-Southern Oscillation (ENSO) (18–23). As a result of the dependence on these lower-frequency phenomena, the average frequency of tropical cyclones can vary within a basin at periods of years to decades.

1.2 Natural disasters under climate change

Improving our understanding of the health risks associated with floods and tropical cyclones (TCs) is particularly important given the chance that changing climate could increase the frequency or intensity of these types of disasters in certain regions over the coming decades. In the past few decades, there has been considerable work done to investigate the interaction between climate change and meteorological, hydrological, and climatological natural disasters. These studies have focused on two main topics: 1) whether changes in climate have already generated noticeable impacts on natural disaster (i.e., observed trends), typically assessed using historical data, and 2) how climate change might alter patterns in natural disasters in the future, typically assessed using projections output from climate models (24). Here, we discuss the observed trends in the recent past and projected changes in the frequency and characteristics of floods and TCs, with a focus on patterns in China and the United States, the two study areas investigated in the research projects forming this dissertation.

Observed recent trends in floods. In China, recent trends in climate exposures related to flooding vary regionally. While some regions of China (e.g., the North China, Northeast China, and the Yellow River basins) experienced a decrease in the frequency of extreme rainfall events from 1961 to 2009, other regions experienced an increasing trend in these events (25). This observed temporal variability in the frequency of extreme rainfall events is in part attributable to global warming, with some influence as well from patterns in the state of other aspects of the climate system, including the East Asian Monsoon and ENSO (25). In the 50 years from 1961 to 2010, the total precipitation during summer months (June–August) increased in Western China and Southeastern China, but decreased in Northeastern China (26). In the U.S., extreme precipitation events have become more frequent nationally during the past few decades, with increases particularly notable in the Northeast, Midwest, and upper Great Plains regions (4). However, this pattern in increased frequency of extreme precipitation events does not translate directly into an increase in the frequency of river flooding (27), in part because flooding is influenced by a number of factors other than precipitation, including drainage of the affected area, land use, and prior soil conditions. While most of the U.S. experienced little or no change in the frequency of river floods from the 1920s through 2008, some areas showed appreciable changes (27).

Projections of floods. Projections created under different climate change-related scenarios indicate that future patterns in extreme precipitation and flood events will likely vary substantially across China. However, these climate studies are in broad agreement that an increase is expected in China in the intensity of the extreme precipitation and flood events that will occur in the future as a result of climate change. For example, one study used coupled general circulation models (CGCMs) to create projections under three emissions scenarios and found that, while some regions of China (e.g., Southern China and the Yangtze River area) were projected to have extreme precipitation events that are both more frequent and intense in the coming century, the Northern and Northeastern regions of China were only projected to experience an increase in the intensity of extreme precipitation events, but not in their frequency (28). In another study, based on the simulations generated by 22 global climate models and a regional climate model, most parts of China were projected to experience flood events that are more frequent, more intense, and longer (29).

Observed trends in tropical cyclones. There is clear evidence from climate studies that the intensity, frequency, and duration of TCs in the Atlantic basin has increased since the early 1980s; further, there is evidence of an increased frequency over this period of the most intense TCs in this basin (Saffir-Simpson Category 4 and 5 storms) (24,30). Recent studies have also found evidence that TCs have had a pattern of decreasing average forward (translational) speed of the storms, with a 10% decrease in this forward storm speed globally, and a 20% decrease when Atlantic basin TCs are over land, between 1949 and 2016 (31). This storm characteristic can play an important role in the potential human impacts of TCs, because the speed of a storm's forward motion is generally related to the amount of rainfall from the storm, as evidenced by the unprecedented rainfall associated with Hurricane Harvey in Texas in 2017 (32) and Hurricane Florence in 2018 (33).

Projections of tropical cyclones. TCs are driven by phenomena at a geographic scale that is smaller than can be easily captured by global-scale climate models. Because of this geographic scale of the phenomena key to TCs, climate projections of TC patterns under future scenarios can vary substantially across studies, as a result of differences in downscaling techniques and model resolutions and algorithms. The majority of such projection studies suggest that TCs will likely become less frequent (e.g., an estimated 16% decrease in frequency from one study), but the TCs that do occur will on average be more intense (projected 3.6% increase in average TC intensity) and have higher precipitation rates (projected increase of 5–20%) by the end of the 21th century (14,34). Further, very intense TCs (e.g., Saffir-Simpson Category 4 and 5 storms) are expected to become more frequent (35). Projections in TC trends differ between the basin that spawn TCs. For example, while the average intensity of Atlantic-basin hurricanes (maximum sustained wind > 33 m/s) is expected to increase by 4.5% by the late of the 21th century, the average intensity of such storms in the southwest Pacific basin is expected to decrease by 3.1% over the same period (14). Improving climate projections of expected trends in TC patterns is an area of continuing research, and projections of trends within specific basins continue to disagree substantially across projections generated from different climate models (24).

2. Health impacts of natural disasters

2.1 Assessing disaster-attributable mortality and morbidity

Natural disasters can cause a range of public health consequences, including mortality, injuries, and infectious disease. According to CRED, a disaster death tool is counted as the "number of people who lost their life because the event happened (it includes also the missing people based on official figures)" (36), while disaster injuries are defined by this international epidemiology center as the "number of people suffering from physical injuries, trauma or an illness requiring immediate medical treatment as a direct result of a disaster" (36). Traditionally, estimates of the number of deaths and injuries related to a natural disaster have been determined based on disaster surveillance (5,37,38), an approach that considers the attribution of the cause or causes of each death in a disaster-exposed geographic area and time period on a case-by-case basis. Such analysis will often result in estimated death and injury tolls both for the entire disaster period and also categorized by disaster phase (pre-, during-, and post-disaster) (39).

Disaster surveillance. Disaster surveillance has been conventionally used as a tool to generate the total estimates of injuries, morbidity, and mortality occurred during and in the aftermath of disasters (37). Existing disaster epidemiologic studies on health impacts of disasters, as discussed in the next subsections ("Current epidemiological evidence on health impacts of floods and TCs"), are generally based on the information provided by disaster surveillance. Depending on the information collected, disaster surveillance is also sometimes referred to as morbidity (including injury and illness) surveillance or mortality surveillance. Four types of disaster surveillance can be conducted during disasters, including passive surveillance, active surveillance, sentinel surveillance, and syndromic surveillance (37,40). Given the specific situation and the feasibility of conducting surveillance during a disaster, a combination of different surveillance activities is often used to provide accurate and complete public health information.

The primary purpose of this surveillance is typically to provide essential public health information during a disaster. To achieve this, disaster surveillance typically includes: 1) collecting health data, based on a specific case definition, from a population of interest; 2) analyzing and interpreting the collected data; and 3) disseminating the data and analyzed results to public health practice (37). For the first element, data can be collected from a variety sources, including health care facilities, records from medical examiner/coroner, poison centers, vital statistics, American Red Cross, Federal Emergency Management Agency, and news media (37,41). Case definition is a very important consideration conducting disaster surveillance. Public officials have been recommended to take into consideration both the direct and indirect health effects in establishing case definitions for disaster surveillance activities (37,42). The U.S. CDC provides a comprehensive reference guide to help death certifiers (e.g., medical examiners and coroners) to classify whether a death occurring during a disaster period is disaster-related (43). This guide recommends two checks: 1) did the death occur in the geographic area affected by the disaster?; and 2) if so, can the death be directly linked to the disaster (i.e., is it a "death caused by the direct physical forces of the hazard or event" (43)) or linked indirectly to the disaster (i.e., was the death "a consequence of the unsafe or unhealthy conditions created by the hazard or event, or by preparations for or cleanup after the natural hazard of event, or by performing work to minimize consequences of the disaster" (43))? Deaths meeting these criteria should be identified as disaster-related on the death certificate; these disaster indications can then be used to collect all death certificates for deaths attributable to the disaster in generating the disaster's fatality toll.

Since disaster surveillance is the main tool of generating overall estimates of disaster-related morbidity and mortality in affected areas, it has been traditionally the basis for many large-scale studies investigating flood- and TC-related mortality and morbidity (5,38,44–48), including research on trends in deaths and injuries associated with these disasters over time, health impacts by country and region, major causes of flood- and TC-related fatalities, and potential risk factors for adverse health consequences.

However, disaster surveillance, though it plays a very important role in effectively responding to disasters, is likely to be subject to several limitations with respect to quantifying the full scale of health impacts associated with exposure to natural disasters. First, because of the lack of a standardized form in collecting and reporting health data in disaster surveillance activities, health officials use different criteria in classifying a health outcome as "disaster-related" (42,49–51), making it difficult to aggregate results across studies of different disasters. Second, surveillance activities can struggle to estimate accurate prevalence or incidence rates due to lack of denominator data or complete counts. Furthermore, surveillance activity, by collecting only information on deaths that occurred during and after a disaster, may miss any pattern of potential avoided death during a disaster. For example, people may stay at home instead of going outside in high-risk condition like tropical cyclones (52), so the potential death risks in driving would be reduced. Patients may no longer be exposed to any surgical risks if hospitals have cancelled scheduled surgeries due to power outages (53). Finally, surveillance evaluates whether a death or injury was "disaster-related" on a case-by-case basis (50,54) and so may not be able to capture the overall community-wide health effects associated with exposure to a disaster if for some of the disaster-related deaths it is difficult to establish the causal chain between the disaster and the death. This is especially of concern if many of the excess events during a disaster were outcomes that are also common outside of disaster periods (e.g., heart attacks, respiratory problems), outcomes that are harder for public health surveillance system to classify on a case-by-case basis as "disaster-related", compared to well-characterized disaster-related risks (e.g., drowning and fracture) (55). There is some evidence that natural disasters are likely to elevate these common causes of morbidity and mortality (56–58), and recent evidence has highlighted this critical gap in our understanding of health risks from disaster exposure (56,59–61).

The recent controversy about the total deaths caused by Hurricane Maria in Puerto Rico has underscored the potential for underestimation disaster-related deaths by traditional disaster surveillance methods. Hurricane Maria made landfall in Puerto Rico on September 20, 2017. On December 9, 2017, the initial official death toll was 64 (62), based on counts of death certificates with "hurricane-related" appearing as the direct cause of death (63). Later in the year, based in part on strong anecdotal evidence that the official fatality toll severely underestimated the full mortality impacts of the storm, a number of independent investigations, including media reports, attempted to estimate the excess mortality in the post-hurricane period through other methods (64). For example, a randomized survey of households across Puerto Rico estimated that 4,645 excess all-cause deaths were attributable to hurricane between September 20 and December 31, 2017 (64). In another study, the excess mortality was estimated for the period from September 2017 to February 2018 in an independent assessment (65), in which the authors compared the observed mortality with expected mortality predicted from generalized linear model using previous seven years data, with adjustment for time trend of population characteristics and the massive population displacement following the hurricane. In August 2018, the Government of Puerto Rico officially revised the death toll to 2,975 (68), more than 60 times of the initial official toll of 64 deaths. Therefore, to complement results from this traditional surveillance approach, critical information is needed to improve current understanding of health risks in natural disasters.

2.2 Current epidemiological evidence on health impacts of floods

Several systematic reviews have been conducted to aggregate study findings on floods and human health (5,44–46). The magnitude of impacts varies between populations due to factors relating to flood types, flood characteristics, effectiveness of warning and evacuation, and population vulnerability (3,45). Worldwide between 1980 and 2009, 539,811 deaths and 361,974 injuries were attributed to floods (5), with Asia and Africa the two regions most frequently struck by floods (2). In 2010, floods caused 2,100 deaths in Pakistan and another 1,900 in China (2). In the U.S., between 1959 and 2005 a total of 4,586 fatalities (not including deaths in Louisiana from Hurricane Katrina) were caused by flooding (69).

Drowning has been identified as the primary cause of flood-related deaths (5). One study investigated 13 flood events in the U.S. and Europe and found that, of all flood-attributable deaths, approximately two thirds were caused by drowning, with others caused by trauma (about 10%) and heart attacks (about 5%), among other causes (70). Several U.S.-based studies also found evidence that a number of flood-related deaths were tied to use of motor vehicles during the flood (71–73), and flood-related deaths from diarrheal diseases have been reported in several studies, although these results remain inconsistent across studies (74–76). In terms of non-fatal outcomes, the primary cause of flood-associated morbidity are non-fatal injuries and exacerbation of chronic medical conditions (77,78). Many other types health consequences have also been reported as associated with floods in previous studies, including communicable and non-communicable diseases (79,80) and mental health issues (81).

2.3 Current epidemiological evidence on health impacts of TCs

Worldwide from 1980 to 2009, 412,644 deaths and 290,654 injuries were attributed to TCs (38). In the U.S. during the 50 years from 1963 to 2012, about 2,500 direct deaths (47) were identified as attributable to TCs, and in a subset of the TCs in that period, about 1,800 deaths were indirectly linked to the TCs (48). For the direct deaths identified in the U.S. as resulting from TCs, drowning and other water-related incidents accounted for the vast majority (approximately 90% of the identified direct TC deaths) (47). Common pathways for the link between TCs and indirect deaths included problems associated with power or power outages (e.g., carbon monoxide poisoning due to misuse of a portable generator, electrocutions), car accidents and other motor vehicle-related pathways, and evacuations (48). Indirect impacts of TCs on human health could also come through infectious disease outbreaks related to storm-damaged sanitation systems (83) and mental health outcomes, including post-traumatic stress disorder in both adults (84) and adolescents (85).

3. A brief description of the study design used in this dissertation

To help respond to research gaps in current knowledge on the health impacts of floods and TCs, here we aim to estimate the overall community-wide change in the rates of health outcome rates from exposure to natural disasters, compared to the expected rates had the disasters not occurred. In framing our research question in this way, we are using a potential-outcomes (or counterfactual) paradigm: ideally, we would measure the community-wide health outcome rates both during the observed disaster exposures and during the same days, but without disaster exposure (i.e., the second potential outcome, or the counterfactual), and compare the difference in these rates as a causal effect estimate of the effect of disaster exposure on these health outcome rates (86–90).

In a study of the effects of disaster exposure on community health outcome rates, the residents of the community that form the study population can be conceptually divided into four groups (Shown in Table 1.1; based on the Table 8.1 in (90) and the ideas in (91)): Group 1: those who would always have the health outcome (D), regardless of exposure to the disaster; Group 2: those who would have the health outcome under disaster exposure but would not have it (ND) otherwise; Group 3: those who would have the health outcome without disaster exposure but would not have it with disaster exposure; and Group 4: those who would never have the health outcome, with or without disaster exposure. When considering rare outcomes like death or hospitalization, most community residents will fall into Group 4. Members of Group 3 might include community residents who, for example, were scheduled for a surgery on the day of the disaster and would have died during the surgery had the disaster not occurred, but for whom the surgery is cancelled because of the storm; this group could also include community residents who would have died from a car accident had the storm not hit the community but stayed home and avoided this outcome because of the storm. Members of Group 2 include most of the deaths counted in official fatality tolls based on disaster surveillance, for which the causal chain from disaster exposure to death can be established for that specific case, but may also include some deaths (e.g., from common causes like cardiorespiratory deaths, deaths among the very frail) that also would not have occurred during the study days without the disaster, but for which it is difficult in surveillance to establish the causal link with the disaster, and so have been missed in official fatality tolls.

Table 1.1 Distribution of possible health outcome as a result of exposed/unexposed to disaster in a population of size N (= N1 + N2 + N3 + N4), reproduced from Table 8.1 in (90) and based on the ideas in (91)*

Group	Exposed to disaster	Unexposed to disaster	Number	Proportion of the population
1	D	D	N1	P1
2	D	ND	N2	P1
3	ND	D	N3	P3
4	ND	ND	N4	P4

*D represents developing the health outcome of interest, and ND represents not developing the health outcome of interest.

In an idealized study, we could measure health outcomes for the full study population both during disaster exposure and under the counterfactual of the disaster failing to hit the community (e.g., collect all information required to calculate all values of N and P in Table 1.1). With these measurements, we could directly determine the probability of the health outcome of interest when everyone is exposed to disaster as P1+P2, and the probability of the health outcome when no one is exposed to disaster as P1+P3. Then the causal relative risk is the ratio of these two probabilities. In reality, it is impossible to observe both potential outcomes, and so we must find a different way to try to determine how disaster exposure affected the probability of a given health outcome.

The study design we used in the research in this dissertation is a matched-analysis approach, in which we compared the health outcome rates during each identified exposed day (i.e., flood- or TC-exposed day) to matched unexposed days in other years, with matching by community and time of year (more details given in the Methods sections of the next Chapters). We also applied model control in analyses to control for potential confounding from yearly trends and day of week. By matching disaster-exposed days with similar unexposed days in the same community, we are attempting to approximate the unobserved counterfactual health outcome distribution (i.e., in the absence of a disaster in the community) on the exposed days using the observed health outcome distribution on these matched unexposed days.

This approximation will never be exact, but can be effective in estimating a causal effect if the population of the community on the exposed day and the matched unexposed days are, or come close to being, exchangeable. The population on the disaster-exposed days and matched unexposed days are exchangeable if their health outcome distribution would be identical when they experience identical exposure (86,87). When using matched days from other years to measure health outcome rates in the unexposed state, the fact that the exposed and unexposed populations are from different years is a key threat to this exchangeability. As a consequence, the estimate of the effect of disaster exposure on risk of the health outcome may be subject to confounding. The most important confounding in this study design stems from temporal variation in many characteristics of study population, such as age distribution, socioeconomic status, and chronic disease rate. To address the confounding in our disaster-health signal, we adjusted for year in the regression model to estimate the association of interest. Details in adjusting confounding and possibility of residual confounding are discussed in the next Chapters.

Therefore, although we are theoretically framing our design in terms of causal inference, we used traditional regression models rather than causal inference methods in statistical analysis. As a result, we will interpret our estimated results as associational instead of causal effects, and in Chapter 5 we discuss potential limitations of our study design in estimating the association between disaster exposure and community-wide health outcome rates. There has recently been a conversation in the context of air pollution epidemiology about whether assessing causal validity should focus exclusively on using causal inference methods (92,93). Dominici and Zigler argued that causality assessment in air pollution epidemiology should focus “most importantly on the design decisions that render the analysis of observational data an approximation of the analysis of a randomized experiment” (92), including design decisions regarding both the study design and analytical decisions. Such a focus emphasizes thoughtful considerations of how to make best use of available data to construct an adequate comparison group, and to use the framework of potential outcomes to explore potential for biases introduced by those design decisions, regardless of whether the methods used to analyze the data are traditional regression methods or causal inference methods.

4. Objectives of this dissertation

The overarching goal of this dissertation is to examine the community-wide effects of natural disasters on some common health outcomes. Specifically, we estimate the associations between: 1) a severe flood of July 21, 2012, and all-cause, accidental, circulatory, and respiratory mortality in Beijing, China; 2) Atlantic-basin tropical cyclones and all-cause, accidental, cardiovascular, and respiratory morality in eastern U.S. communities, 1988–2005; and 3) Atlantic-basin tropical cyclones and cardiovascular and respiratory hospitalizations among Medicare beneficiaries in eastern U.S. communities, 1999–2010.

References

1. Below R, Wirtz A, Guha-Sapir D. Disaster category classification and peril terminology for operational purposes. Common accord Centre for Research on the Epidemiology of Disasters (CRED) and Munich Reinsurance Company (Munich RE). Working Paper 264, UCL; 2009.

2. Wahlstrom M, Guha-Sapir D. The human cost of weather-related disasters 1995–2015. *United Nations Office for Disaster Risk Reduction*. 2015;

3. Jonkman S, Vrijling J. Loss of life due to floods. *Journal of Flood Risk Management*. 2008;1(1):43–56.

4. Melillo JM, Richmond T, Yohe GW, et al. Highlights of Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program; 2014.(http://s3.amazonaws.com/nca2014/high/NCA3_Highlights_HighRes.pdf?download=1)

5. Doocy S, Daniels A, Murray S, et al. The human impact of floods: A historical review of events 1980-2009 and systematic literature review. *PLoS Currents Disasters*. 2013;

6. Zong Y, Chen X. The 1998 flood on the Yangtze, China. *Natural Hazards*. 2000;22(2):165–184.

7. Wang K, Wang L, Wei Y-M, et al. Beijing storm of July 21, 2012: Observations and reflections. *Natural Hazards*. 2013;67(2):969–974.

8. Zhou T, Song F, Lin R, et al. The 2012 North China floods: Explaining an extreme rainfall event in the context of a longer-term drying tendency. *Bulletin of the American Meteorological Society*. 2013;94(9):S49.

9. Lyu H-M, Wang G-F, Shen J, et al. Analysis and GIS mapping of flooding hazards on 10 May 2016, Guangzhou, China. *Water*. 2016;8(10):447.

10. Emanuel K. Tropical cyclones. *Annual Review of Earth and Planetary Sciences*. 2003;31(1):75–104.

11. Jarvinen BR, Caso EL. A tropical cyclone data tape for the North Atlantic basin, 1886–1977: Contents, limitations, and uses. *NOAA Technical Memorandum NWS NHC-6*. 1978;

12. Halverson JB. Second wind: The deadly and destructive inland phase of east coast hurricanes. *Weatherwise*. 2015;68(2):20–27.

13. Webster PJ, Holland GJ, Curry JA, et al. Changes in tropical cyclone number, duration, and intensity in a warming environment. *Science*. 2005;309(5742):1844–1846.

14. Knutson TR, Sirutis JJ, Zhao M, et al. Global projections of intense tropical cyclone activity for the late twenty-first century from dynamical downscaling of CMIP5/RCP4.5 scenarios. *Journal of Climate*. 2015;28(18):7203–7224.

15. Schott T, Landsea C, Hafele G, et al. The Saffir-Simpson hurricane wind scale. *NOAA/National Weather Service [Internet]*. 2012;1–4.

16. Chris Landsea (National Hurricane Center). How many hurricanes have there been in each month? 2016;(http://www.aoml.noaa.gov/hrd/tcfaq/E17.html)

17. Leroy A, Wheeler MC. Statistical prediction of weekly tropical cyclone activity in the Southern Hemisphere. *Monthly Weather Review*. 2008;136(10):3637–3654.

18. Camargo SJ, Barnston AG, Klotzbach PJ, et al. Seasonal tropical cyclone forecasts. *World Meteorological 0rganization Bulletin*. 2007;56(4):297.

19. Dare RA, McBride JL. The threshold sea surface temperature condition for tropical cyclogenesis. *Journal of Climate*. 2011;24(17):4570–4576.

20. Chan JC. Tropical cyclone activity over the western North Pacific associated with El Niño and La Niña events. *Journal of Climate*. 2000;13(16):2960–2972.

21. Wang H, Long L, Kumar A, et al. How well do global climate models simulate the variability of Atlantic tropical cyclones associated with ENSO? *Journal of Climate*. 2014;27(15):5673–5692.

22. Diamond HJ, Lorrey AM, Renwick JA. A southwest Pacific tropical cyclone climatology and linkages to the El Niño–Southern Oscillation. *Journal of Climate*. 2013;26(1):3–25.

23. Bell R, Hodges K, Vidale PL, et al. Simulation of the global ENSO–tropical cyclone teleconnection by a high-resolution coupled general circulation model. *Journal of Climate*. 2014;27(17):6404–6422.

24. Walsh KJ, McBride JL, Klotzbach PJ, et al. Tropical cyclones and climate change. *Wiley Interdisciplinary Reviews: Climate Change*. 2016;7(1):65–89.

25. Fu G, Yu J, Yu X, et al. Temporal variation of extreme rainfall events in China, 1961–2009. *Journal of Hydrology*. 2013;487:48–59.

26. Lu E, Zeng Y, Luo Y, et al. Changes of summer precipitation in China: The dominance of frequency and intensity and linkage with changes in moisture and air temperature. *Journal of Geophysical Research: Atmospheres*. 2014;119(22):12–575.

27. Peterson TC, Heim Jr RR, Hirsch R, et al. Monitoring and understanding changes in heat waves, cold waves, floods, and droughts in the United States: State of knowledge. *Bulletin of the American Meteorological Society*. 2013;94(6):821–834.

28. Chen H, Sun J, Chen X, et al. CGCM projections of heavy rainfall events in China. *International Journal of Climatology*. 2012;32(3):441–450.

29. Huo-Po C, Jian-Qi S, Xiao-Li C. Future changes of drought and flood events in China under a global warming scenario. *Atmospheric and Oceanic Science Letters*. 2013;6(1):8–13.

30. Walsh J, Wuebbles D, Hayhoe K, et al. Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program; 2014.

31. Kossin JP. A global slowdown of tropical-cyclone translation speed. *Nature*. 2018;558(7708):104.

32. Emanuel K. Assessing the present and future probability of Hurricane Harvey's rainfall. *Proceedings of the National Academy of Sciences*. 2017;201716222.

33. Meyer R. Hurricane Florence's Slow Speed Is Ominous. 2018;(https://www.theatlantic.com/science/archive/2018/09/hurricane-florence-and-the-fear-of-a-stalled-out-storm/569953/)

34. Knutson TR, McBride JL, Chan J, et al. Tropical cyclones and climate change. *Nature Geoscience*. 2010;3(3):157.

35. Bender MA, Knutson TR, Tuleya RE, et al. Modeled impact of anthropogenic warming on the frequency of intense Atlantic hurricanes. *Science*. 2010;327(5964):454–458.

36. EM-DAT Glossary. 2009;(https://www.emdat.be/Glossary)

37. Centers for Disease Control and Prevention (CDC). A Primer for Understanding the Principles and Practices of Disaster Surveillance in the United States. *Atlanta (GA): CDC*. 2016;

38. Doocy S, Dick A, Daniels A, et al. The human impact of tropical cyclones: A historical review of events 1980–2009 and systematic literature review. *PLoS Currents Disasters*. 2013;

39. Centers for Disease Control and Prevention. Medical examiner/coroner reports of deaths associated with Hurricane Hugo–South Carolina. *MMWR: Morbidity and Mortality Weekly Report*. 1989;38(44):754–759.

40. Stone K, Horney JA. Chapter 2 - Methods: Surveillance. In: Horney JA, ed. *Disaster epidemiology*. Academic Press; 2018:11–23.(http://www.sciencedirect.com/science/article/pii/B9780128093184000022)

41. Noe RS. Chapter 5 - Applications: Disaster-Related Mortality Surveillance: Challenges and Considerations for Local and State Health Departments. In: Horney JA, ed. *Disaster epidemiology*. Academic Press; 2018:55–63.

42. Combs DL, Quenemoen LE, Parrish RG, et al. Assessing disaster-attributed mortality: Development and application of a definition and classification matrix. *International Journal of Epidemiology*. 1999;28(6):1124–1129.

43. National Center for Health Statistics. A reference guide for certification of deaths in the event of a natural, human-induced, or chemical/radiological disaster. Hyattsville, MD: 2017.
44. Alderman K, Turner LR, Tong S. Floods and human health: A systematic review. *Environment International*. 2012;47:37–47.
45. Ahern M, Kovats RS, Wilkinson P, et al. Global health impacts of floods: Epidemiologic evidence. *Epidemiologic Reviews*. 2005;27(1):36–46.
46. Saulnier DD, Ribacke KB, von Schreeb J. No calm after the storm: A systematic review of human health following flood and storm disasters. *Prehospital and Disaster Medicine*. 2017;32(5):568–579.
47. Rappaport EN. Fatalities in the united states from Atlantic tropical cyclones: New data and interpretation. *Bulletin of the American Meteorological Society*. 2014;95(3):341–346.
48. Rappaport EN, Blanchard BW. Fatalities in the united states indirectly associated with Atlantic tropical cyclones. *Bulletin of the American Meteorological Society*. 2016;97(7):1139–1148.
49. Combs DL, Parrish RG, McNABB SJ, et al. Deaths related to Hurricane Andrew in Florida and Louisiana, 1992. *International Journal of Epidemiology*. 1996;25(3):537–544.
50. Centers for Disease Control and Prevention. Mortality associated with Hurricane Katrina–Florida and Alabama, August–October 2005. *Morbidity and Mortality Weekly Report*. 2006;55(9):239–242.
51. Centers for Disease Control and Prevention. Injuries and illnesses related to Hurricane Andrew–Louisiana, 1992. *Morbidity and Mortality Weekly Report*. 1993;42(13):242–4.
52. Naumann RB, Dellinger AM, Kresnow M-j. Driving self-restriction in high-risk conditions: How do older drivers compare to others? *Journal of Safety Research*. 2011;42(1):67–71.
53. Gray BH, Hebert K. Hospitals in Hurricane Katrina: Challenges facing custodial institutions in a disaster. *Journal of Health Care for the Poor and Underserved*. 2007;18(2):283–298.
54. Sharif HO, Jackson TL, Hossain MM, et al. Analysis of flood fatalities in Texas. *Natural Hazards Review*. 2014;16(1):04014016.
55. Domino ME, Fried B, Moon Y, et al. Disasters and the public health safety net: Hurricane Floyd hits the North Carolina Medicaid program. *American Journal of Public Health*. 2003;93(7):1122–1127.
56. Swerdel JN, Janevic TM, Cosgrove NM, et al. The effect of Hurricane Sandy on cardiovascular events in New Jersey. *Journal of the American Heart Association*. 2014;3(6):e001354.
57. Mortensen K, Dreyfuss Z. How many walked through the door?: The effect of Hurricane Katrina evacuees on Houston emergency departments. *Medical Care*. 2008;46(9):998–1001.
58. Gotanda H, Fogel J, Husk G, et al. Hurricane Sandy: Impact on emergency department and hospital utilization by older adults in Lower Manhattan, New York (USA). *Prehospital and Disaster Medicine*. 2015;30(5):496–502.
59. Howland RE, Li W, Madsen AM, et al. Evaluating the use of an electronic death registration system for mortality surveillance during and after Hurricane Sandy: New York City, 2012. *American Journal of Public Health*. 2015;105(11):e55–e62.
60. Santos-Lozada AR, Howard JT. Use of death counts from vital statistics to calculate excess deaths in Puerto Rico following Hurricane Maria. *Journal of the American Medical Association*. 2018;
61. Mongin SJ, Baron SL, Schwartz RM, et al. Measuring the impact of disasters using publicly available data: Application to Hurricane Sandy (2012). *American Journal of Epidemiology*. 2017;186(11):1290–1299.
62. Aumentan a 64 muertes certificadas por maría. 2017;(https://www.telemundopr.com/noticias/destacados/Aumentan-a-64-las-muertes-por-el-huracan-Maria-463005263.html)
63. Santos-Lozada AR, Howard JT. Use of death counts from vital statistics to calculate excess deaths in Puerto Rico following Hurricane Maria. *Journal of the American Medical Association*. 2018;

64. Kishore N, Marques D, Mahmud A, et al. Mortality in Puerto Rico after Hurricane Maria. *New England Journal of Medicine* [electronic article]. 2018;(https://doi.org/10.1056/NEJMsa1803972)

65. Santos-Burgoa C, Goldman A, Andrade E, et al. Acertainment of the estimated excess mortality from Hurricane Maria in Puerto Rico. 2018;

66. Robles F, Davis K, Almukhtar S. Official Toll in Puerto Rico: 64. Actual Deaths May Be 1,052. 2017;(https://www.nytimes.com/interactive/2017/12/08/us/puerto-rico-hurricane-maria-death-toll.html)

67. Rivera R, Rolke W. Estimating the death toll of Hurricane Maria. *Significance*. 2018;15(1):8–9.

68. Puerto Rico increases Hurricane Maria death toll to 2,975. 2018;(https://www.bbc.com/news/world-us-canada-45338080?intlink_from_url=&link_location=live-reporting-story)

69. Ashley ST, Ashley WS. Flood fatalities in the United States. *Journal of Applied Meteorology and Climatology*. 2008;47(3):805–818.

70. Jonkman SN, Kelman I. An analysis of the causes and circumstances of flood disaster deaths. *Disasters*. 2005;29(1):75–97.

71. Centers for Disease Control and Prevention. Storm-related mortality–central Texas, October 17–31, 1998. *Morbidity and Mortality Weekly Report*. 2000;49(7):133–135.

72. Staes C, Orengo JC, Malilay J, et al. Deaths due to flash floods in Puerto Rico, January 1992: Implications for prevention. *International Journal of Epidemiology*. 1994;23(5):968–975.

73. Centers for Disease Control and Prevention. Flood-related mortality–Georgia, July 4–14, 1994. *Morbidity and Mortality Weekly Report*. 1994;43(29):526.

74. Yusof A, Siddique A, Baqui A, et al. 1988 floods in Bangladesh: Pattern of illness and causes of death. *Journal of Diarrhoeal Diseases Research*. 1991;310–314.

75. Woodruff BA, Toole MJ, Rodrigue DC, et al. Disease surveillance and control after a flood: Khartoum, Sudan, 1988. *Disasters*. 1990;14(2):151–163.

76. Kunii O, Nakamura S, Abdur R, et al. The impact on health and risk factors of the diarrhoea epidemics in the 1998 Bangladesh floods. *Public Health*. 2002;116(2):68–74.

77. Diaz J. The public health impact of hurricanes and major flooding. *The Journal of the Louisiana State Medical Society*. 2004;156(3):145–150.

78. Ohl CA, Tapsell S. Flooding and human health: The dangers posed are not always obvious. *BMJ: British Medical Journal*. 2000;321(7270):1167.

79. Reacher M, McKenzie K, Lane C, et al. Health impacts of flooding in Lewes: A comparison of reported gastrointestinal and other illness and mental health in flooded and non-flooded households. *Communicable Disease and Public Health*. 2004;7(1):39–46.

80. Arrieta MI, Foreman RD, Crook ED, et al. Providing continuity of care for chronic diseases in the aftermath of katrina: From field experience to policy recommendations. *Disaster Medicine and Public Health Preparedness*. 2009;3(3):174–182.

81. Ginexi EM, Weihs K, Simmens SJ, et al. Natural disaster and depression: A prospective investigation of reactions to the 1993 Midwest floods. *American Journal of Community Psychology*. 2000;28(4):495–518.

82. Centers for Disease Control and Prevention. Update: Work-related electrocutions associated with Hurricane Hugo–Puerto Rico. *MMWR: Morbidity and Mortality Weekly Report*. 1989;38(42):718–20.

83. Bissell RA. Delayed-impact infectious disease after a natural disaster. *Journal of Emergency Medicine*. 1983;1(1):59–66.

84. Ironson G, Wynings C, Schneiderman N, et al. Posttraumatic stress symptoms, intrusive thoughts, loss, and immune function after Hurricane Andrew. *Psychosomatic Medicine*. 1997;59(2):128–141.

85. Garrison CZ, Weinrich MW, Hardin SB, et al. Post-traumatic stress disorder in adolescents after a hurricane. *American Journal of Epidemiology*. 1993;138(7):522–530.

86. Greenland S, Robins JM. Identifiability, exchangeability, and epidemiological confounding. *International Journal of Epidemiology*. 1986;15(3):413–419.
87. Greenland S, Robins JM. Identifiability, exchangeability and confounding revisited. *Epidemiologic Perspectives & Innovations*. 2009;6(1):4.
88. Höfler M. Causal inference based on counterfactuals. *BMC Medical Research Methodology*. 2005;5(1):28.
89. Zigler CM, Dominici F. Point: Clarifying policy evidence with potential-outcomes thinking—beyond exposure-response estimation in air pollution epidemiology. *American Journal of Epidemiology*. 2014;180(12):1133–1140.
90. Jewell NP. Statistics for Epidemiology. Chapman; Hall/CRC; 2003.
91. Rothman KJ, Greenland S, Lash TL. Modern Epidemiology. Modern Epidemiology, 3rd Edition. Philadelphia, PA: Lippincott Williams & Wilkins; 2008.
92. Dominici F, Zigler C. Best practices for gauging evidence of causality in air pollution epidemiology. *American Journal of Epidemiology*. 2017;186(12):1303–1309.
93. Cox LA. Re:"Best practices for gauging evidence of causality in air pollution epidemiology". *American Journal of Epidemiology*. 2018;187(6):1338–1339.

Chapter 2: Changes in the community-wide rates of all-cause, circulatory, respiratory, and accidental mortality in Beijing, China during the July 2012 flood

1. Chapter overview

On July 21–22, 2012, Beijing, China, suffered its heaviest rainfall in 60 years. The average rainfall was 170 mm across Beijing and reached 460 mm in the Fangshan District in less than 24 hours, causing heavy flooding throughout Beijing. While two studies have estimated the fatality toll of this disaster based on a traditional surveillance approach of assessing deaths during the event case-by-case, this approach can be prone to miss some disaster-related deaths, particularly for deaths from common non-accidental causes, and would fail to identify any patterns in avoided deaths during the disaster. Therefore, to complement results from this traditional surveillance approach, we aimed to investigate how community-wide mortality rates differed during this flood from the rates expected had the flood not occurred. To do so, we conducted a matched analysis comparing mortality rates on the peak flood day and the four following days to similar unexposed days in previous years (2008–2011), controlling for potential confounders, to estimate the relative risks (RRs) of daily mortality among Beijing residents associated with this flood. Compared to the matched unexposed days, mortality rates were substantially higher during the flood period for all-cause, circulatory, and accidental mortality, with the highest risks observed on the peak flood day. On the peak flood day, the flood-associated relative risks of mortality were 1.34 (95% confidence interval: 1.11–1.61), 1.37 (1.01–1.85), and 4.40 (2.98–6.51) for all-cause, circulatory, and accidental mortality, respectively. No evidence of increased risk of respiratory mortality was observed in this study. We estimated a total of 79 excess deaths among Beijing residents on July 21–22, 2012; by contrast, only 34 deaths were reported among Beijing residents in a study estimating the fatality toll of this flood using a traditional surveillance approach. Results were robust to study design and modeling choices. Our results indicate considerable impacts of this flood on public health, and that much of this impact may come from increased risk of non-accidental deaths. To our knowledge, this is the first study analyzing the community-wide changes in mortality rates during the 2012 flood in Beijing, and one of the first to do so for any major flood worldwide. This study offers critical evidence in assessing flood-related health impacts, as urban flooding is expected to become more frequent and severe in China.

2. Introduction

On July 21–22, 2012, Beijing, China, suffered its heaviest rain in 60 years (1,2). The average rainfall was 170 mm across Beijing; in the Fangshan District, the district with heaviest rainfall, 460 mm of rain fell in 18 hours (1). By comparison, in Beijing the typical total precipitation for the whole month of July is 160.5 mm (3). This extreme rainfall caused extensive flooding in Beijing.

Two studies (4,5) estimated the fatality toll from this flood, using a traditional surveillance approach of investigating each death that occurred in Beijing during the flood period, case-by-case, to identify which were flood-attributable. Based on this approach, 60 or more of the deaths in Beijing (including both residents and non-residents) on July 21–22, 2012, were attributable to the flood, mostly from drowning. However, this traditional surveillance approach can undercount disaster-associated deaths, especially from causes that are common outside of disaster periods (6). Further, it is unable to identify any patterns of potential avoided deaths during the disaster (e.g., a reduction in automobile fatalities related to people avoiding driving during severe weather conditions (7)). Given these limitations in the traditional surveillance approach, critical complementary information on disaster-associated health risks can be provided by assessments that investigate changes in mortality rates throughout the disaster-affected community, comparing observed rates during the disaster to the rates expected had the disaster not occurred.

While assessments of community-wide mortality rates have been used to help understand the health impacts of other climate-related disasters, especially extreme temperature and heat waves (e.g., (8,9)), very few studies have used a similar technique to better understand the mortality risks associated with floods. Several previous studies have explored large-scale, multi-year patterns in flood-related fatality tolls, including in the United States (10) and Australia (11), but these employed a traditional surveillance approach. Worldwide, a few studies (e.g., (12–16)) have investigated flood-associated mortality risks by comparing the rate of community-wide mortality observed during the flood to that in non-flooded periods or areas. These studies have generally found important increases in community-wide mortality rates during and following severe floods. For example, a 47% increase in monthly mortality rates was observed in New Orleans, LA, in the period following Hurricane Katrina and its related flooding compared to other years (13), while a controlled survey of the 1968 flood in Bristol reported a 50% increase in all-cause mortality among the affected population in the 12 months after the flood (14). However, evidence on how community-wide mortality rates change during severe floods remains extremely limited, including in China.

These community-wide assessments can be particularly helpful in capturing changes in rates of circulatory and respiratory mortality during a disaster, as both are common mortality outcomes outside of disaster periods and so hard to attribute to a disaster on a case-by-case basis. Limited studies from outside China have found floods can substantially increase the risk of non-fatal cardiorespiratory outcomes, making it plausible that major floods could also increase community-wide rates of circulatory and respiratory deaths. For example, a typhoon-induced flood in South Korea was associated with elevated risks of heart palpitations (17), while a 1-in-180-year flood in Carlisle, England, exacerbated existing chronic conditions for many people, resulting in adverse health outcomes related to heart attacks and dementia (18).

Beijing's large population (> 21 million (19)) provides the power to investigate how a major flood changed community-wide mortality rates during and immediately after the event, both for deaths from all causes and for deaths from several specific causes (circulatory, respiratory, and accidental). Our analysis complements existing knowledge of how floods affect human health based on studies conducted using the traditional surveillance approach. In particular, our approach provides estimates that are less likely to undercount non-accidental disaster-associated deaths and that could identify any potential patterns of avoided mortality during the flood.

3. Methods

Data

We obtained daily mortality counts from the Chinese Center for Disease Control and Prevention (CDC) for all Beijing residents from January 1, 2008, to December 31, 2012. Cause of death was coded according to the International Classification of Disease, Revision 10 (ICD-10, 2003 version) (20). We aggregated data to create daily community-wide counts of deaths from four causes: all-cause, accidental (ICD-10: S00–Z99), circulatory (I00–I99), and respiratory (J00–J99). We obtained residential population data from the National Bureau of Statistics of China (19). We obtained daily temperature data from a weather station located in Nanjiao District and daily average concentrations of particulate matter with an aerodynamic diameter ≤ 2.5 micrometers (PM) (used in sensitivity analysis) from a station in the Haidian District, both administrated by the Beijing Meteorological Bureau.

Statistical Analysis

The methodology is still in development for estimating how community-wide mortality rates during and immediately after a disaster differ from expected rates had the disaster not occurred. One potential approach is to use the study designs common in studying ambient exposures like air pollution and temperature, including time series (e.g., (8,21)) and time-stratified case-crossover study designs (e.g., (22,23)). However, when investigating risks associated with a discrete disaster period, rather than a continuous exposure, a potential limitation of both of these approaches is that they include unexposed days that are close in time to the disaster, including days immediately after the disaster. This element of both study designs could lead to biased estimates if disasters have extended impacts on community-wide health risks beyond the modeled period of risk. Such extended impacts have been observed following previous major disasters; a recent example is that the mortality rate in Puerto Rico was 62% higher throughout the three months following Hurricane Maria compared with the same period the year before (24). Given these potential concerns with applying time series and case-crossover study designs to analyze the effects of a disaster, we instead used a study design that matches the days of the flood disaster to similar unexposed days from the same time of the year in other years, with control for long-term trends in mortality rates and the influence of temperature on mortality risk incorporated in the statistical model fit to this matched data. As a sensitivity analysis, we also estimated risks based on time series and case-crossover designs, to help determine the sensitivity of estimates to the choice of study design.

We matched the day of worst flooding (*peak flood day*, July 21, 2012), as well as four days after the peak flood day, with similar unexposed days. For the matched unexposed days, we selected days that were in: 1) a different year than the flood year; 2) the same month of year as the flood (July); and 3) the same day of week as the exposed day. To these matched data, we fit a model incorporating a distributed lag approach to estimate the immediate and short-term relative risks (RRs) of this flood on daily community-wide mortality rates in Beijing while controlling for the potential confounders of long-term trends in mortality rates and temperature's influence on mortality risk. We fit the following generalized linear model to the matched data:

$$\log[E(Y_t)] = \log(n_t) + \alpha + \sum_{l=0}^{4} \beta_l x_{t-l} + \gamma Year_t + \delta T_t \tag{2.1}$$

where:

- Y_t is the daily mortality among all Beijing residents on day *t*;
- n_t is the residential population of Beijing in the year of day *t*, included as an offset term to capture variation in Beijing's population over the study period;
- α is the model intercept;
- β_l (*l = 0, …, 4*) are the coefficients estimated from an unconstrained distributed lag function of flood exposure (25). x_t is 1 for the peak flood day and 0 for other days, and therefore x_{t-l} is an indicator variable denoting whether a given day at lag *l* from day *t* is within the flood-exposed period or within the matched unexposed period;

- $Year_t$ is the year for day *t*, with γ as the coefficient for year, allowing control for a linear trend in mortality rates across study years;
- T_t is the mean temperature for day *t*, with δ as the coefficient for T_t.

The estimated lag-specific RRs of mortality on lag *l* from the peak flood day were calculated as $exp(\widehat{\beta_l})$, based on the values of $\widehat{\beta_l}$ estimated from eq. 2.1. To estimate the excess deaths attributable to the flood on each day of the flood period, we calculated (26):

$$\hat{E}_l = Y_l(\frac{RR_l-1}{RR_l}) \tag{2.2}$$

where:

- $\hat{E}_l$ is the estimated excess death count at lag *l* from the peak flood day;
- Y_l is the observed death count at lag *l* from the peak flood day;
- RR_l is the estimated lag-specific RR, calculated based on the value of $\hat{\beta}_l$ estimated from eq. 2.1.

Previous research that calculated the fatality tolls for this flood using a traditional surveillance method (4,5) determined their fatality tolls for the two days of July 21–22, 2012, since the extreme rain started at noon on July 21 and ended on the morning of July 22. Therefore, to allow us to compare estimated flood-associated fatality tolls between our analysis approach and the traditional surveillance method, we also calculated excess deaths specifically for these two days. We calculated confidence interval for the estimate of total excess deaths on this two-day period through Monte Carlo simulations (48) (details in Appendix A, "Supplementary material for Chapter 2").

Sensitivity analysis. In additional to our primary analysis, we also conducted sensitivity analyses to help determine the sensitivity of estimates to study design and modeling choices. First, we investigated whether results changed with differing selections of control days: we changed to select from any day of the same month of year as the flood (July) in other years (i.e., without a day-of-week restriction; referred to as "Matching by month"). Second, we investigated the results of changing model control for potential confounders. We first adjusted for the daily average concentration of fine particulate matter (PM) ("PM-adjusted"). We next fit a model that did not adjust for temperature as in the primary analysis ("Not temperature-adjusted"). Finally, we investigated the sensitivity of effect estimates to using time series and case-crossover designs rather than matching to similar days from other years. In the time series analysis ("Time series"), we used a natural cubic spline function of time with 7 degree of freedom per year in the model to control for seasonal and long-term trends and, to control for temperature, a natural cubic spline with 3 degree of freedom over the entire study period. In the case-crossover analysis ("Case-crossover"), we used the time-stratified variant of this design (23), defining the case day as the peak flood day and control days as those days in the same year, month of year, and day of week as the case day.

4. Results

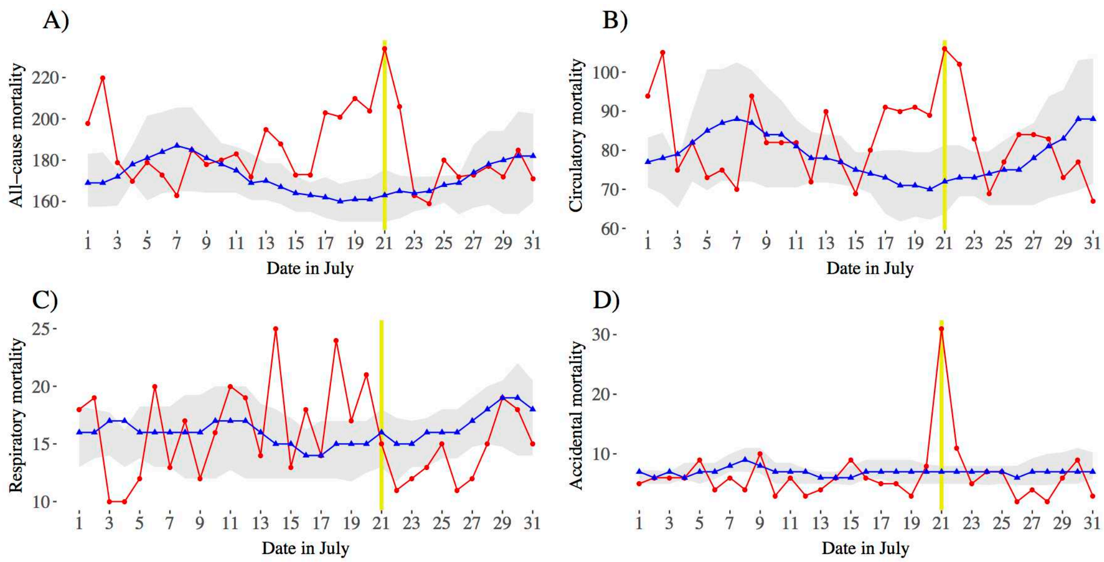

Figure 2.1 Daily mortality counts for Beijing residents in July 2012 (red) compared with average mortality counts in July of previous years for (A) all-cause mortality, (B) circulatory mortality, (C) respiratory mortality, and (D) accidental mortality. Shown for comparison are the mean (blue line) and interquartile range (grey area) of the five-day moving average of mortality counts in July of the four previous years (2008–2011). The yellow vertical lines show the peak flood day (July 21).

Table 2.1 Estimates of relative risk of mortality compared to expected mortality rates had the flood not occurred, as well as resulting estimates of flood-associated excess deaths, among Beijing residents on the peak flood day (July 21, 2012) and the following day. For each point estimate, 95% confidence intervals are shown in parentheses.

	Relative risk on July 21, 2012 (peak flood day)	Relative risk on July 22, 2012	Excess deaths on peak flood day*	Excess deaths on July 21–22, 2012#
All-cause mortality	1.34 (1.11, 1.61)	1.11 (0.91, 1.35)	59 (23, 89)	79 (22, 125)
Circulatory mortality	1.37 (1.01, 1.85)	1.22 (0.90, 1.65)	28 (1, 49)	46 (6, 79)
Respiratory mortality	0.94 (0.52, 1.72)	0.64 (0.32, 1.28)	-1 (-14, 6)	-7 (-29, 5)
Accidental mortality	4.40 (2.98, 6.51)	1.49 (0.82, 2.71)	24 (21, 26)	28 (20, 32)

*Confidence intervals were calculated based on the uncertainty of estimated relative risk on the peak flood day.
#Confidence intervals were calculated using Monte Carlo simulation (details in Appendix A).

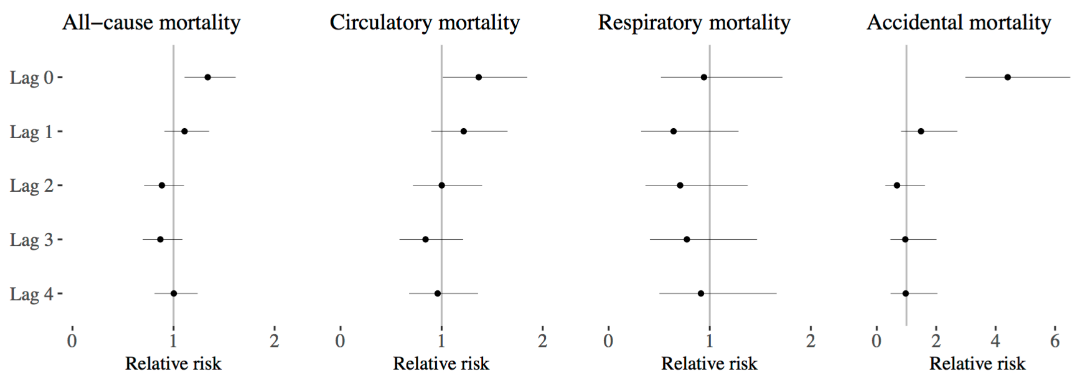

Figure 2.2 Estimates of the relative risk of mortality for four mortality outcomes on the peak flood day (lag 0) and on the four following days (lags 1–4) compared with matched unexposed days from other years, with modeled control for temperature and long-term mortality trends. Dots show point estimates and horizontal lines show 95% confidence intervals. The gray vertical line shows as a reference a relative risk of 1.

Table 2.2 Sensitivity of estimates of relative risks of mortality on the peak flood day (July 21, 2012) to study design and modeling choices. The first row repeats the estimates generated based on our primary analysis (also shown in Table 2.1). All other rows show estimates based on alternative study design or modeling choices; see the Methods for descriptions of each. Shown in parentheses are the 95% confidence intervals for each estimate.

	All-cause mortality	Circulatory mortality	Respiratory mortality	Accidental mortality
Primary analysis	1.34 (1.11, 1.61)	1.37 (1.01, 1.85)	0.94 (0.52, 1.72)	4.40 (2.98, 6.51)
Matching by month	1.35 (1.11, 1.63)	1.38 (1.01, 1.88)	0.91 (0.50, 1.66)	3.86 (2.70, 5.54)
$PM_{2.5}$-adjusted	1.33 (1.09, 1.62)	1.32 (0.97, 1.79)	0.90 (0.49, 1.66)	4.55 (2.96, 6.98)
Not temperature-adjusted	1.27 (1.02, 1.57)	1.28 (0.92, 1.77)	0.88 (0.48, 1.64)	4.22 (2.87, 6.21)
Time series	1.30 (1.11, 1.52)	1.33 (1.06, 1.67)	0.93 (0.55, 1.56)	5.48 (3.73, 8.06)
Case-crossover	1.33 (1.09, 1.62)	1.38 (1.04, 1.83)	0.85 (0.46, 1.57)	6.64 (3.48, 12.67)

Community-wide mortality rates were substantially higher among Beijing residents during the flood period for all-cause, circulatory, and accidental mortality compared to rates in matched unexposed periods (Figures 2.1 and 2.2). The highest increased risks were observed on the peak flood day (July 21, 2012) (Figures 2.1 and 2.2), when the relative risks (RRs) of community-wide mortality rates compared to matched unexposed days were 1.34 (95% confidence interval (CI): 1.11–1.61), 1.37 (1.01–1.85), and 4.40 (2.98–6.51) (Figure 2.2), for all-cause, circulatory, and accidental mortality, respectively. These relative risks translated to 59 flood-related excess deaths overall on the peak flood day among Beijing residents, including 28 excess circulatory deaths and 24 excess accidental deaths (Table 2.1). For respiratory mortality, conversely, there was no evidence of an increase in the community-wide rate during the flood compared to matched unexposed days.

The increases in community-wide rates for all-cause, circulatory, and accidental mortality were largest on the peak flood day (July 21, 2012), with some evidence of a continued increase in mortality rates on the day following the flood (Figure 2.2). For the days considered further after the peak flood day (lags 2–4), we did not find evidence of significantly increased mortality risk for any mortality cause considered. For the two-day period considered in calculating the fatality toll for this flood in traditional surveillance studies (July 21–22, 2012), we estimated a total of 79 excess deaths among Beijing residents (Table 2.1). Most of these deaths were from circulatory causes (an estimated 46 flood-related deaths) or accidental deaths (an estimated 28 flood-related deaths) (Table 2.1).

Estimates of RRs were robust to modeling choice and the matching method for selecting unexposed days, with estimates especially consistent for all-cause, circulatory, and respiratory mortality (Table 2.2). However, when considering accidental mortality, we found greater RR point estimates for these estimates, when using time series and time-stratified case-crossover designs compared with our primary design of matching to control days from other years (Table 2.2). This could be because the accidental mortality rate in July varied across the years included in the study in a non-linear pattern that was difficult to capture using a linear control for long-term patterns in mortality rates (Figure A1), as done in our primary analysis. Thus, residual confounding was likely to occur within our primary estimates of RRs for accidental mortality (More details in Chapter 5).

5. Discussion

Our results demonstrate this flood's considerable impacts on public health in Beijing, with much of this impact resulting from increased risk of non-accidental mortality, in particular circulatory mortality. The government of China, using a traditional surveillance approach of identifying flood-related deaths on a case-by-case basis, identified 60 flood-related deaths (among Beijing residents and non-residents combined) on July 21–22, 2012 (4). Another study that similarly used a traditional surveillance approach—expanding on the government analysis by combining fatality information on specific deaths from different sources like government reports and site visitations—identified 71 flood-related deaths during this period, 34 of which were among Beijing residents (5). This estimated fatality toll among Beijing residents based on the traditional surveillance approach is less than half the number of flood-related deaths we estimated based on an approach of comparing community-wide mortality rates during July 21–22, 2012, to the rates expected had the flood not occurred (Table 2.1).

Further, the previous surveillance-based research found the majority of flood-attributable deaths were due to drowning (4,5). Research based on the surveillance approach did identify two circulatory deaths from the flood—two people who died in conducting rescues because of excessive work and heart failure (5). While we similarly estimated a substantial toll from accidental deaths (28 excess accidental deaths estimated for July 21–22), we also found an important increase in non-accidental mortality during the flood period, with 46 excess circulatory deaths estimated for July 21–22 (Table 2.1), an impact largely missed through the traditional surveillance method. The increased risk during the flood for circulatory deaths, and its associated impact, can be much more difficult to capture using the traditional disaster surveillance method than accidental deaths (e.g., drowning deaths). This is in part because circulatory deaths are not directly caused by the physical forces of the flood and in part because circulatory deaths are not rare outside of flood periods, making it harder to declare that a specific circulatory death would not have occurred without the flood.

The flood-related circulatory deaths we observed could have resulted in part from the flood disrupting health services through associated damage to infrastructure (such as transportation and communications). During this period in Beijing, many roads and bridges were flooded (about 63 main roads in Beijing (27)), crowded with fallen building and trees, and even destroyed (27). Infrastructure damage can prevent residents from reaching healthcare resources, which is especially dangerous among people with pre-existing chronic medical conditions, or hinder medical personnel from offering services (28–30). Beijing's dense population and heavy reliance on public transportation make it particularly susceptible to these complications. In addition, flooding can be an emotional trigger that exacerbates the initiating process of acute cardiac events (31), an effect that has been identified for other types of disasters including earthquakes (32) and human-caused disasters (33). Flood-related deaths from circulatory causes have also been reported in flood events in England (18), Bangladesh (34), and France (35), and a retrospective study of 1997 floods in the Czech Republic found the rates of cardiac-related mortality in the month of flood was more than twice the rate in the two previous months (16).

Conversely, we did not find a short-term association between respiratory mortality and this flood. Studies have found the likelihood of indoor mold growth increases in months following major floods (36), and indoor dampness or mold has been shown to be consistently associated with respiratory problems (37). Thus, while we found no evidence of an association between this flood and immediate respiratory mortality rates, the flood might still increase risk of respiratory mortality in a longer period (e.g., months) than that investigated here. A few epidemiological studies have found increased longer-term risk of respiratory problems and infections among people in flood-affected areas (15,34,38,39). For example, in Bangladesh, about half of respondents (46.8%) in two affected districts reported developing or suffering exacerbation of respiratory problems in the two months following the 1998 flood (34), and approximately 13% of reported deaths in the two months following the country's 1988 flood were attributed to respiratory disease (39). Further, six months after the 2004 floods in rural Bangladesh, a moderate increased risk of acute respiratory infection (RR = 1.25, 95% CI, 1.06–1.47) was observed when comparing flooded versus unflooded areas (15).

The increased mortality risks we identified occurred primarily on the peak flood day (July 21), with lower mortality risks on the following day and little or no evidence of elevated risks on the days following that (Figure 2.2). This pattern in risks lagging the flood may, however, be specific to this Beijing flood, which varied in some key characteristics from other major floods that have been studied. Although this flood event was extreme for Beijing (the heaviest rainfall in six decades), it results from an extreme precipitation event that was much shorter (< 24 hours) and had a much lower total rainfall than other major flood events like the two-month flooding in Bangladesh in 1998 (34). Further, in the most affected districts of Beijing (e.g., Fangshan District), most residents were evacuated within a day of the flooding (27), which may have helped prevent additional flood-related deaths on the following days. Flood characteristics can be important in determining patterns in flood-associated health risks (35,40); future research could explore whether community-wide flood mortality risks, including patterns in lagged effects following the flood, can be partially explained by variation in factors like the duration of rainfall and the community's emergency response measures.

One limitation of this study is that we were unable to explore district-level mortality risks and impacts of this flood, as mortality data at the district level were not available. The intensity of this rainfall was heterogeneous across Beijing (4,41); for example, the average hourly precipitation on July 21–22 in the Fangshan District (in the southwest of Beijing) was 15.2 mm, while in the Huairou District (northeast of Beijing) it was 5.7 mm (4). Based on one of the studies that analyzed this event using a traditional disaster surveillance method (4), the amount of rainfall in a person's neighborhood was found to be an important factor in the risks of flood-related mortality, a pattern we are unable to explore using city-level data. A second limitation stems from the difficulty of estimating the community-wide expected mortality rate had the flood not occurred, for which we used the mortality rate in similar days from previous years. Given our finding that there was little evidence of elevated mortality risk by the second day following the flood, our initial concern about use of the time series and case-crossover designs to study this event—that they might be prone to bias based on the inclusion of days classified as unexposed to the event within the period of plausible extended disaster effects—is unlikely to be a problem in studying this event. Indeed, in sensitivity analyses (Table 2.2), we found our key conclusions (an approximately 30% increased risk in all-cause mortality associated with the flood, with important contributions from both circulatory and accidental deaths) were robust across all study designs considered, adding weight to these conclusions, although choices among study design added some uncertainty to the exact quantitative estimates of risks and associated impacts, particularly for accidental mortality outcomes.

Recent and expected climate trends make it critical to improve our understanding of the health risks associated with climate-related disasters, including floods, in order to help limit the health impacts of future events. Our study city, Beijing, is located in the North China Plain, where although the amount and frequency of rainfall have decreased over the last decades (42,43), the intensity of heavy rainfall is projected to increase substantially over the next few decades (44). Although flood events as severe as the one investigated in this study have to date been rare in Beijing, floods of similar magnitude may be more common in the coming decades. Throughout China, most regions have experienced an increasing trend in the frequency of extreme rainfall events (1961–2009) (43) and are expected to experience an increased frequency of severe flood events through the end of 21 century (45), as are many other locations worldwide (e.g., Europe (46) and the Midwest and Northeast regions of U.S. (47)). This study, and similar studies estimating the community-wide change in mortality rates during flood events, can add to existing studies of flood-related mortality based on a traditional surveillance method to offer critical evidence in assessing flood-related health impacts and crafting strategies to limit or prevent flood-related deaths during future events.

References

1. Zhang D, Lin Y, Zhao P, et al. The Beijing extreme rainfall of 21 July 2012: 'Right results' but for wrong reasons. *Geophysical Research Letters*. 2013;40(7):1426–1431.

2. BBC. Beijing chaos after record floods in Chinese capital. 2012;(https://www.bbc.com/news/world-asia-china-18942984). (Accessed July 23, 2018)

3. Zhou T, Song F, Lin R, et al. The 2012 North China floods: Explaining an extreme rainfall event in the context of a longer-term drying tendency. *Bulletin of the American Meteorological Society*. 2013;94(9):S49.

4. Liu J, Wang S-Y. Analysis of human vulnerability to the extreme rainfall event on 21–22 July 2012 in Beijing, China. *Natural Hazards and Earth System Sciences*. 2013;13(11):2911–2926.

5. Du W, FitzGerald G, Hou X-Y, et al. A case study in flood fatality: Beijing July 2012 flood. In: *Proceedings of the 9th Annual International Conference of the International Institute for Infrastructure Renewal and Reconstruction, Risk-informed Disaster Management*. 2013

6. McKinney N, Houser C, Meyer-Arendt K. Direct and indirect mortality in Florida during the 2004 hurricane season. *International Journal of Biometeorology*. 2011;55(4):533–546.

7. Naumann RB, Dellinger AM, Kresnow M-j. Driving self-restriction in high-risk conditions: How do older drivers compare to others? *Journal of Safety Research*. 2011;42(1):67–71.

8. Anderson GB, Bell ML. Heat waves in the United States: Mortality risk during heat waves and effect modification by heat wave characteristics in 43 US communities. *Environmental Health Perspectives*. 2011;119(2):210.

9. Gasparrini A, Guo Y, Hashizume M, et al. Mortality risk attributable to high and low ambient temperature: A multicountry observational study. *The Lancet*. 2015;386(9991):369–375.

10. Ashley ST, Ashley WS. Flood fatalities in the United States. *Journal of Applied Meteorology and Climatology*. 2008;47(3):805–818.

11. FitzGerald G, Du W, Jamal A, et al. Flood fatalities in contemporary Australia (1997–2008). *Emergency Medicine Australasia*. 2010;22(2):180–186.

12. Milojevic A, Armstrong B, Kovats S, et al. Long-term effects of flooding on mortality in England and Wales, 1994-2005: Controlled interrupted time-series analysis. *Environmental Health*. 2011;10(1):11.

13. Stephens KU, Grew D, Chin K, et al. Excess mortality in the aftermath of Hurricane Katrina: A preliminary report. *Disaster Medicine and Public Health Preparedness*. 2007;1(1):15–20.

14. Bennet G. Bristol floods 1968. controlled survey of effects on health of local community disaster. *British Medical Journal*. 1970;3(5720):454.

15. Milojevic A, Armstrong B, Hashizume M, et al. Health effects of flooding in rural Bangladesh. *Epidemiology*. 2012;107–115.

16. Obrová J, Sovová E, Ivanová K, et al. Effects of the July 1997 floods in the Czech Republic on cardiac mortality. *Disaster Medicine and Public Health Preparedness*. 2014;8(6):492–496.

17. Chae E-H, Kim TW, Rhee S-J, et al. The impact of flooding on the mental health of affected people in South Korea. *Community Mental Health Journal*. 2005;41(6):633–645.

18. Carroll B, Balogh R, Morbey H, et al. Health and social impacts of a flood disaster: Responding to needs and implications for practice. *Disasters*. 2010;34(4):1045–1063.

19. National Bureau of Statistics of China. National data. 2016;(http://data.stats.gov.cn/english/easyquery.htm?cn=E0103). (Accessed June 1, 2018)

20. World Health Organization. International Statistical Classification of Diseases and Related Health Problems, 10th Revision. World Health Organization; 2003.(http://apps.who.int/classifications/apps/icd/icd10online2003/fr-icd.htm)

21. Schwartz J, Marcus A. Mortality and air pollution in London: A time series analysis. *American Journal of Epidemiology*. 1990;131(1):185–194.
22. Neas LM, Schwartz J, Dockery D. A case-crossover analysis of air pollution and mortality in Philadelphia. *Environmental Health Perspectives*. 1999;107(8):629.
23. Gronlund CJ, Zanobetti A, Schwartz JD, et al. Heat, heat waves, and hospital admissions among the elderly in the United States, 1992–2006. *Environmental Health Perspectives*. 2014;122(11):1187.
24. Kishore N, Marques D, Mahmud A, et al. Mortality in Puerto Rico after Hurricane Maria. *New England Journal of Medicine*. 2018;
25. Gasparrini A. Modeling exposure-lag-response associations with distributed lag non-linear models. *Statistics in Medicine*. 2014;33(5):881–899.
26. Steenland K, Armstrong B. An overview of methods for calculating the burden of disease due to specific risk factors. *Epidemiology*. 2006;17(5):512–519.
27. Wang K, Wang L, Wei Y-M, et al. Beijing storm of July 21, 2012: Observations and reflections. *Natural Hazards*. 2013;67(2):969–974.
28. Du W, FitzGerald GJ, Clark M, et al. Health impacts of floods. *Prehospital and Disaster Medicine*. 2010;25(3):265–272.
29. Schatz JJ. Floods hamper health-care delivery in southern Africa. *The Lancet*. 2008;371(9615):799–800.
30. Axelrod C, Killam PP, Gaston MH, et al. Primary health care and the Midwest flood disaster. *Public Health Reports*. 1994;109(5):601.
31. Steptoe A, Kivimäki M. Stress and cardiovascular disease. *Nature Reviews Cardiology*. 2012;9(6):360.
32. Leor J, Kloner RA. The Northridge earthquake as a trigger for acute myocardial infarction. *The American Journal of Cardiology*. 1996;77(14):1230–1232.
33. Steinberg JS, Arshad A, Kowalski M, et al. Increased incidence of life-threatening ventricular arrhythmias in implantable defibrillator patients after the World Trade Center attack. *Journal of the American College of Cardiology*. 2004;44(6):1261–1264.
34. Kunii O, Nakamura S, Abdur R, et al. The impact on health and risk factors of the diarrhoea epidemics in the 1998 Bangladesh floods. *Public Health*. 2002;116(2):68–74.
35. Ruin I, Creutin J-D, Anquetin S, et al. Human exposure to flash floods–Relation between flood parameters and human vulnerability during a storm of September 2002 in Southern France. *Journal of Hydrology*. 2008;361(1-2):199–213.
36. Barbeau DN, Grimsley LF, White LE, et al. Mold exposure and health effects following Hurricanes Katrina and Rita. *Annual Review of Public Health*. 2010;31:165–178.
37. Mendell MJ, Mirer AG, Cheung K, et al. Respiratory and allergic health effects of dampness, mold, and dampness-related agents: A review of the epidemiologic evidence. *Environmental Health Perspectives*. 2011;119(6):748.
38. Biswas R, Pal D, Mukhopadhyay S. A community based study on health impact of flood in a vulnerable district of West Bengal. *Indian Journal of Public Health*. 1999;43(2):89–90.
39. Siddique A, Baqui A, Eusof A, et al. 1988 floods in Bangladesh: Pattern of illness and causes of death. *Journal of Diarrhoeal Diseases Research*. 1991;310–314.
40. Jonkman SN, Maaskant B, Boyd E, et al. Loss of life caused by the flooding of New Orleans after Hurricane Katrina: Analysis of the relationship between flood characteristics and mortality. *Risk Analysis*. 2009;29(5):676–698.
41. Jin MS, Li Y, Su D. Urban-induced mechanisms for an extreme rainfall event in Beijing China: A satellite perspective. *Climate*. 2015;3(1):193–209.

42. Zhang S, Huang G, Wang J, et al. Impact of urban surface characteristics on summer rainfall in the Beijing–Tianjin–Hebei area. *Chinese Journal of Atmospheric Sciences*. 2015;39(5):911–925.
43. Fu G, Yu J, Yu X, et al. Temporal variation of extreme rainfall events in China, 1961–2009. *Journal of Hydrology*. 2013;487:48–59.
44. Chen H, Sun J, Chen X, et al. CGCM projections of heavy rainfall events in China. *International Journal of Climatology*. 2012;32(3):441–450.
45. Huo-Po C, Jian-Qi S, Xiao-Li C. Future changes of drought and flood events in China under a global warming scenario. *Atmospheric and Oceanic Science Letters*. 2013;6(1):8–13.
46. Alfieri L, Feyen L, Dottori F, et al. Ensemble flood risk assessment in Europe under high end climate scenarios. *Global Environmental Change*. 2015;35:199–212.
47. Melillo JM, Richmond T, Yohe GW, et al. Highlights of Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program; 2014. (http://s3.amazonaws.com/nca2014/high/NCA3_Highlights_HighRes.pdf?download=1)
48. Gasparrini A, Leone M. Attributable risk from distributed lag models. *BMC Medical Research Methodology*. 2014;14(1):55.

Chapter 3: Tropical cyclones and associated risks to all-cause, accidental, cardiovascular, and respiratory mortality in 70 United States communities, 1988–2005

1. Chapter overview

While risks of accidental deaths from tropical cyclones (e.g., drowning) have been well-documented using a traditional case-by-case surveillance approach, much less is known about mortality risks from more common causes of death (e.g., cardiorespiratory), for which specific deaths can be hard to attribute to a storm. To provide complementary information to existing knowledge, we analyzed the community-wide change in mortality rates during storms compared with expected rates in the communities had the storms not occurred. We assessed tropical cyclone exposure using five metrics——distance to storm track; cumulative rainfall; maximum sustained wind speed; flooding events; and tornado events. For each exposure metric, we modeled the association between community-level tropical cyclone exposure and daily death counts of residents in 78 large eastern United States (U.S.) communities (1988–2005) using a matched analysis of storm-exposed days versus similar unexposed days. Ninety-two tropical cyclones were considered based on U.S. landfall or close approach, with 70 communities exposed to at least one storm. Under tropical cyclone wind exposures, mortality risks were generally elevated, with highest risks typically on the day of the storm's closest approach. For the strongest wind exposures, relative risks (RRs) of mortality on the day of storm's closest approach were 1.42 (95% CI, 1.36–1.49), 12.03 (10.87–13.32), 1.15 (1.06–1.24), 1.12 (0.92–1.38) for all-cause, accidental, cardiovascular, and respiratory mortality, respectively, across all exposed communities. These estimated associations may be dominated by extremely high risks during the few most severe tropical cyclone wind exposures; for example, a RR of 38.69 (7.37–203.21) was observed for cardiovascular mortality during Hurricane Katrina in New Orleans. Our analysis of community-wide mortality risks from tropical cyclones adds two important insights to results from traditional surveillance: first, the health impact of tropical cyclone exposures on non-accidental mortality can, in some cases, be much greater than identified in case-by-case surveillance studies and, second, intense wind exposures characterize many of the tropical cyclones with particularly high associated risks of non-accidental mortality.

2. Introduction

The East and Gulf Coasts of the United States (U.S.) are commonly exposed to powerful and destructive hurricanes and other tropical cyclones, and the average intensity of tropical cyclones, as well as the frequency of the strongest storms in the Atlantic basin, are expected to increase under climate change by the late 21th century (1–3). Numerous studies have estimated fatality tolls during tropical cyclones in the U.S., and explored trends in these tolls (4–8), using a traditional surveillance approach. This traditional surveillance approach typically involves collecting information on every death that occurs in a storm-affected area during and in the aftermath of a tropical cyclone, and then classifying whether each of those deaths was directly or indirectly related to the storm based on death certificates and other information that can be found about the causes of each specific death (9).

However, limitations exist regarding the fatality tolls estimated using this traditional surveillance approach. First, coroners and medical examiners use different criteria in classifying a death as storm-related, making it difficult to quantitatively aggregate findings across tropical cyclones and communities (10,11). Second, surveillance activity, by collecting only information about deaths that occurred during the storm period, may miss any pattern of potential avoided deaths during this period. For example, people may stay at home instead of going outside in high-risk condition like tropical cyclones (12), so the potential community-wide risks of death related to driving may be reduced. Patients may no longer be exposed to surgical risks they may otherwise have had without the storm, because hospitals storm-related power outages can cause hospitals to cancel scheduled surgeries (13). Third, while the traditional surveillance method can do a good job in counting deaths from some specific causes clearly related to tropical cyclones (e.g., trauma and drowning), the approach may undercount the total number of storm-related deaths, especially undercounting deaths from natural causes that are also common outside of tropical cyclones (e.g., cardiovascular and respiratory deaths).

The recent controversy regarding the total deaths caused by Hurricane Maria provides a striking example of a case where the traditional surveillance approach may have dramatically undercounted tropical cyclone-related deaths. On September 20, 2017, Hurricane Maria made landfall in Puerto Rico. On December 9, 2017, the initial official death toll was 64 (14), based on death certificates with "hurricane-related" appearing as the direct cause of death (15). After that, a number of independent investigations, including media reports, have attempted to estimate the excess mortality in the post-hurricane period using other approaches (15–19). For example, a randomized survey of households across Puerto Rico estimated that 4,645 total excess deaths in Puerto Rico between September 20 and December 31, 2017, were attributable to Hurricane Maria (16). Another study took another approach, comparing observed mortality in the year of the storm with expected mortality without the storm, as predicted from a generalized linear model based on data from the previous seven years and with adjustment for time trends in population characteristics and massive population displacement from Puerto Rico following the hurricane (17). This study similarly found a dramatically higher number of excess deaths attributable to Hurricane Maria than estimated in the original official death toll. As a result of these studies, the Government of Puerto Rico officially changed the death toll of this storm to be 2,975 (20), more than 60 times the original official count (64).

Considering these limitations of the traditional surveillance approach, important complementary information on storm-related mortality risks can be provided by assessing the change in community-wide mortality rates during a tropical cyclone compared to the expected rates had the storm not occurred. Although such community-wide assessments have been used to study the health risks associated with other natural disasters, especially heat waves (21–23), such assessments have seldom been used to help understand the community-wide health impacts from tropical cyclones. Results from the few studies that have used this approach to study tropical cyclones, however, have been striking and have added critical insights to our knowledge of tropical storm health risks based on traditional surveillance studies. For example, according to one community-wide assessment of mortality rates, four 2004 Florida hurricanes were associated with approximately 600 excess deaths, a mortality impact underestimated by surveillance by a factor of more than four (24). Another study found that, in the month following Hurricane Sandy made landfall in New Jersey, all-cause mortality in older residents (>76 years) increased 6%, in comparison to the same time in earlier years (25). Further, a study based on Medicare and Medicaid claims data found that 23% of patients with end-stage renal disease in Hurricane Sandy-affected areas received early dialysis, while during the same time period of previous year, only 6.3% of these patients received this care (26). Almost all of these community-wide assessment studies for tropical cyclones to date, however, were conducted at the single-storm, single-year, or single-community level. The community-wide changes in risk of mortality during tropical cyclones have not been systematically assessed across a large collection of U.S. communities, separate storms, and multiple years.

A systematic community-wide assessment may be particularly useful in clarifying how tropical cyclones might change the risks of mortality from non-accidental deaths, as there are reasons to expect that, like risk of death from accidental causes, risk of non-accidental deaths is also likely to increase during tropical cyclones. Several pathways are hypothesized, including loss of access to emergency service or treatment, increased physical activity (like clean-up), or storm-induced environmental hazard (like air pollution and heat) (27–30). While deaths from non-accidental causes in tropical cyclones were also identified using the traditional surveillance approach (31,32), non-accidental deaths can be difficult to attribute on a case-by-case basis to a disaster (10,33), since such deaths are very common outside of disasters and often have indirect rather than direct links to disaster hazards. In fact, single-storm or single-year studies using community-wide assessments have indeed found evidence suggesting that non-accidental mortality risks during a tropical cyclone could be much higher than identified using the traditional surveillance approach.

To help address these knowledge gaps that result from limitations in the traditional surveillance approach, and in particular for mortality from non-accidental causes that are common outside of a storm, we explored the association between Atlantic basin tropical cyclones and risks of all-cause, accidental, cardiovascular, and respiratory mortality among community residents, comparing mortality rates on storm-exposed days with rates on similar unexposed days in 70 communities in the eastern U.S. between 1988 and 2005. Our results provide information on tropical cyclones and health that is complementary to the extensive previous findings on tropical cyclones and human mortality based on a traditional surveillance approach.

3. Methods

Data

Mortality data. Our study investigated a subset of communities in the National Morbidity, Mortality, and Air Pollution Study (NMMAPS) (34): those 78 communities in this study that are in the eastern half of the U.S. and so susceptible to Atlantic-basin tropical cyclones (Figure 3.1). Each community is either a single county or a group of adjacent counties (34). For each study community, a time series of daily mortality counts was available from 1988 to 2011 for all community residents for four categories of deaths: all-cause (International Classification of Diseases, Ninth Revision (ICD-9), 001–999), accidental (ICD-9, 800–999), cardiovascular (ICD-9 codes 390–448), and respiratory (ICD-9 codes 480–486, 490–497, or 507).

Tropical cyclones. We identified all tropical cyclones that passed within 250 kilometers of at least one eastern U.S. county during study period (1988–2005), using the National Hurricane Center's revised Atlantic hurricane database (HURDAT2) (35). For each tropical cyclone, we measured county-level exposure in the 78 study communities based on five metrics: 1) distance to the storm track, 2) cumulative rainfall, 3) maximum sustained wind speed, 4) occurrence of one or more flood events, and 5) occurrence of one or more tornadoes. Some study communities included two or more adjacent counties. For these communities, we aggregated county-level exposure assessments to the community level by assessing the community as exposed to a storm for a given metric if at least one county in the community qualified as exposed to the storm by that metric.

Distance-based exposure. We first assessed exposure based on distance of the storm's closest approach to the county. For each storm, we interpolated the storm track to a 15-minute interval, from the original six-hour position measurements given in HURDAT2, using a natural cubic spline with number of knots based on the number of available position measurements for that storm (36). We then measured, for each county in the study communities, the distance between the county's population-mean center (37) and each 15-minute estimate of the storm's position. We used the minimum value of this distance as an estimate of the distance between the storm's center and the county center at the storm's closest approach to the county, as well as recorded the date of this closest approach to use in merging with recorded weather data for other exposure assessments. We investigated the mortality risk associated with storm exposure based on a distance-based metric for four thresholds of distance: 25, 50, 75, and 100 km.

Rain-based exposure. To characterize county-level rain exposure to each tropical cyclone, we used precipitation data from the North American Land Data Assimilation System, phase 2 (NLDAS-2) (38), aggregated from its original 1/8th degree grid to the county level (39). This re-analysis dataset integrates from surface observations and satellites and applies a land-surface model to this collection of data to generate a county-level time series of daily precipitation across the continental United States (38,39). We considered a county exposed to a tropical cyclone if 1) cumulative rainfall from one day before to one day after the date of the storm's closest approach to the county surpassed a certain threshold and 2) the county was within 500 km of the storm's track at the storm's closest approach. We explored the health risks associated with rain-based storm exposure as defined using four thresholds for this cumulative three-day precipitation: 50, 75, 100, and 125 mm.

Wind-based exposure. To estimate storm-related winds within each study community for each storm, we modeled ground-level maximum sustained wind speed using a double exponential wind speed model (40). These functions are available as an R software package (41). This model integrates inputs from the HURDAT2 database on the storm's position, direction of movement, forward speed, and maximum 10-meter, 1-minute sustained wind speed to estimate maximum wind speeds associated with the storm at each study community's population mean center as the storm moves near or through the community. From this collection of modeled wind speeds, we identified for each community the highest wind speeds throughout the course of the storm. We explored mortality risks associated with wind-based exposure to tropical cyclones based on four thresholds of maximum storm winds at the county center: 12, 15, 18, and 21 m/s.

Flood- and tornado-based exposure. We assessed county-level exposure to storm-induced floods and tornadoes using storm event data from the National Oceanic and Atmospheric Administration (NOAA)'s Storm Events Database (42). For each tropical cyclone, this Storm Event database was queried for all study counties for which the storm came within 500 km of the county at closest approach. For each of these study communities, we identified all flood and tornado events with a start date within a five-day window of the date of the storm's closest approach to the county. For our assessments based on these exposures, we limited our analysis to 1996 and later, because the NOAA Storm Events database was substantially expanded starting in 1996 and did not include flood events prior to that year.

Three exposure metrics were continuous (distance to the storm track, cumulative rainfall, and maximum sustained wind speed). For these, we considered several thresholds for classifying a county as exposed based on that metric, to allow us to explore the influence of threshold choices on mortality risk estimates. For all tropical cyclone exposure assessments, we used the R packages "*hurricaneexposure*" (36) and "*hurricaneexposuredata*" (43).

Statistical Analysis

A *storm exposure* was defined as the occurrence of a storm bringing conditions to a study community that met one of the storm exposure definitions, based on either distance to the storm track, maximum sustained winds, cumulative rainfall, flooding, or tornadoes. Therefore, a storm could create multiple exposures within our study (if it brought these conditions to multiple study communities), and a study community could experience multiple exposures across the study period, from multiple storms.

For each metric of tropical cyclone exposure, we aimed to estimate across all storm exposures the change in the exposed communities' mortality rates during periods of tropical cyclone exposure compared to expected mortality rates had the storm not hit. To estimate this, we conducted an analysis with a set of matched days, matching the days in which each study community was exposed to tropical cyclones to unexposed days in other years, with matching by community and time of year (more matching details below). Model control was used in analysis of these matched days to control for additional possible confounding related to year and day of the week. Similar study designs have previously been used to estimate the acute health effects of extreme events that occur infrequently and irregularly, including heatwaves (21) and wildfires (44).

Tropical cyclones may influence community health not only on the day of the storm's closest approach to the community, but also a day or two before—as residents prepare for the storm or evacuate—as well as after the storm has passed, as residents deal with clean-up efforts and damaged roads, power systems, and other infrastructure. To estimate the associations between tropical cyclone exposure and mortality risk for a window of days surrounding the day of each storm's closest approach, we incorporated a distributed lag approach, modeling patterns in mortality risks from two days before to seven days after the storm's closest approach. The distributed lag modeling approach has been used extensively in time series and case-crossover environmental epidemiology studies to investigate risks over a period of several days following exposure to an ambient environmental threat (22,23,45,46). Here, we extend this framework to also investigate elevated risk immediately before the day of the storm's closest approach (lags -2 and -1, i.e., one and two days before the storm's closest approach), as well as up to a week after the storm (lags 1 to 7).

Matching. For each tropical cyclone exposure metric considered, we first identified any exposed storm days for each of the study communities. Study communities with no storm exposure days under that metric were excluded from further analysis. Within each community with one or more exposed storm days, we then matched each identified storm day to ten unexposed days, matching by seasonality. These ten matched unexposed days were randomly selected from a pool of candidate unexposed days for the community which: 1) were in a different year; 2) were within a seven-day window of the storm day's day of the year (to match for seasonality); 3) were not within a three-day window of a different storm day for the community; and 4) were not in the two-week period starting on September 11, 2001. For each storm day and its ten matched unexposed days, we pulled the series of days from two days before to seven days after the target day, to allow us to investigate the association between tropical cyclone exposure and mortality risk for a period surrounding the date of a storm's closest approach to a county. For example, if August 31, 2004, was defined as a storm day, then the period from August 29 to September 7, 2004, was pulled as the storm exposure period for that storm in that community, while a period of the same length was pulled surrounding each matched unexposed day. For days in the storm period, the day's lag day was set as the amount of time between that day and the day of the storm's closest approach (e.g., if the storm's closest approach was August 31, 2004, then August 29, 2004 was identified as the lag-2 exposure day for that storm).

Mortality risks of the ten most severe tropical cyclone wind exposures. Atlantic basin tropical cyclones are typically classified in intensity based on the Saffir-Simpson scale, which is primarily based on the storm's maximum wind speeds (47), and a storm's winds have been identified as the main storm hazard associated with damaging infrastructure and buildings (48,49). Therefore, we began with a targeted analysis of the single-storm mortality risks associated with the ten most intense storm exposures, in terms of maximum sustained winds experienced within the community, in communities in our study with a population of at least 400,000. Since death counts from respiratory and accidental causes are generally small in a single community, to achieve adequate statistical power and prevent model convergence issue, we only investigated all-cause and cardiovascular mortality outcomes for these severe storm exposures.

To estimate the relative risk (RR) on the day of storm's closest approach to the community for these ten storm exposures, we used the matching approach described above to create a subset of days to analyze and then fit the a single-community, single-storm generalized linear fixed-effect model to the matched data. We first fit a model to estimate risk specifically on the day of the storm's closest approach, without considering risks on other days in the period surrounding the storm:

$$\log[E(Y_t)] = \log(n) + \alpha + \beta_t x_t + \boldsymbol{\gamma} DOW_t + \delta Year_t \tag{3.1}$$

where:

- Y_t is the daily death count on the day *t*;
- $log(n)$ is an offset term for the residents' population *n* for the community;
- α is the model intercept;
- x_t is an indicator variable of storm exposure ($x = 1$ for storm exposed day and $x = 0$ for matched unexposed day), and β_t is the coefficient for storm exposure on the day of storm's closest approach to community;
- DOW_t is an indicator variable for day of week and $\boldsymbol{\gamma}$ is a vector of regression coefficients for DOW;
- $Year_t$ is the year of day *t*, to account for long-term trend in community's mortality risk across the study period, and δ is the regression coefficient for $Year$.

For these ten storm exposures, we also calculated cumulative RRs, estimating the change in mortality risk during the entire period from two days before to seven days after the day of the storm's closest approach, by fitting the following model:

$$\log[E(Y_T)] = \log(n) + \alpha + \beta_T x_T + \delta Year_T \tag{3.2}$$

where:

- Y_T is the sum of daily death counts during the storm period *T* (i.e., two days before to seven days after the day of storm's closest approach to the community);
- $log(n)$ is an offset term the residents' population *n* for the community;
- α is the model intercept;

- x_T is an indicator variable of storm exposure ($x_T = 1$ for storm exposed period and $x_T = 0$ for the matched unexposed period) and β_T is the coefficient of storm exposure during the period;
- $Year_T$ is the year of the storm period and δ is the coefficient of $Year$.

For each of these ten tropical cyclone exposures, the same-day RRs were estimated as $exp(\hat{\beta}_t)$, based on the values of $\hat{\beta}_t$ estimated by fitting 3.1, and cumulative RRs were estimated as $exp(\hat{\beta}_T)$, based on the values of $\hat{\beta}_T$ estimated by fitting eq. 3.2. We also estimated the number of excess deaths on the day of storm's closest approach as $Y_t(1 - exp(-\hat{\beta}_t))$, as well as the excess deaths for the entire storm period, calculated as $Y_T(1 - exp(-\hat{\beta}_T))$, with Y_t and Y_T as defined in eq. 3.1 and 3.2 (50). As a sensitivity analysis, we also explored the associations for these ten storm exposures, using time series and case-crossover analysis, which have been commonly used in studying the health effects of ambient environmental exposures. Results of this sensitivity analysis are shown in Appendix D.

Mortality risks of all tropical cyclones. Next, we estimated the overall mortality risks associated with all tropical cyclone exposures under a given metric, incorporating all exposed study communities and relevant storms in the study period into the analysis. To do this, we fit the following generalized linear mixed-effect model using the multi-community matched data, in which some of the letters have the same representations as eq.3.1:

$$\log[E(Y_t^c)] = \log(n^c) + \alpha + \alpha^c + \sum_{l=-2}^{7} \beta_l x_{t+l}^c + \boldsymbol{\delta} Year_t + \boldsymbol{\gamma} DOW_t \tag{3.3}$$

where:

- Y_t^c is the daily death count on day *t* for community *c*;
- $log(n^c)$ is an offset term for the population of community *c* in $Year$, the year of day t;
- α^c are random intercepts for each study community, assumed to follow a normal distribution with a mean of 0 and variance of σ^2 (i.e., $\alpha^c \sim N(0, \sigma^2)$);

- $\sum_{l=-2}^{7} \beta_l x_{t+l}^c$ is an unconstrained distributed lag function of the storm exposure variable *x*. β_l is the coefficient estimating the association between tropical storm exposure and mortality at lag *l* from day *t*, the day of the storm's closest approach to study community *c*. x_{t+l}^c is the indicator variable representing whether a given day at lag *l* from day *t* for community *c* is part of an exposed storm period or part of a matched unexposed period.
- $Year_t$ is an indicator variable of year on day *t*, with $\boldsymbol{\delta}$ as a vector of coefficients for $Year$.
- DOW_t is an indicator variable of day of week on day *t*, with $\boldsymbol{\gamma}$ as a vector of coefficients for DOW.

We fit eq. 3.3 separately for each combination of tropical cyclone exposure metric and mortality outcome. For each definition of tropical cyclone exposure, we estimated both lag-specific and cumulative RRs for days in the storm period compared with matched unexposed periods. The lag-specific RRs were calculated as $exp(\hat{\beta}_l)$, based on the values of $\hat{\beta}_l$ estimated by fitting eq. 3.3. We also estimated cumulative RRs, which estimate the cumulative mortality risks across the entire storm exposure period, from two days before to seven days after the day of the storm's closest approach. These cumulative RRs were calculated as $exp(\sum_{l=-2}^{7} \hat{\beta}_l)$, based on the values of $\hat{\beta}_l$ estimated by fitting eq. 3.3 (45).

For all-cause and cardiovascular mortality, we fit eq. 3.3 while including all study communities exposed to at least one storm under a given exposure metric. Since respiratory and accidental deaths are typically less frequent, in estimating tropical cyclone-related risks for these mortality outcomes, we considered only study communities with populations > 400,000, to prevent convergence problems in model fitting. As a sensitivity analysis, to investigate if differences in estimated risks by cause of death were associated with this modeling choice, we also estimated storm-associated risks for all-cause and cardiovascular mortality using this subset of higher-population communities.

Influence of the ten most severe tropical cyclone wind exposures on overall estimates. Finally, we investigated whether estimates of storm-related mortality risk based on the multi-community, multi-storm model were driven mainly by the ten most severe tropical cyclone wind exposures over the study period.

For this subgroup analysis, we fit eq. 3.3 to the subset of all other identified tropical cyclone exposures, excluding the ten most severe tropical cyclone wind exposures, across all study communities with populations > 400,000. When selected matched unexposed days for this analysis, we excluded days from all classified storm exposures under the metric, including days within or near one of the ten most severe tropical cyclone wind exposures. We investigated how the average storm-related mortality risks for this subset of storm exposures compared to the relative risks estimated for the complete set of storm exposures under the main analysis.

4. Results

Over our study period, 92 tropical cyclones passed within 250 kilometers of at least one eastern U.S. county and were considered further in our study (Figure 3.1). Out of 78 study communities considered, 70 communities were exposed to at least one tropical cyclone over our study period (1988–2005), based on at least one of the tropical cyclone exposure metrics considered (Figure 3.1). For all exposure metrics considered, the study covered at least 50 storm exposures; storm exposures were rarest for the most constrictive threshold of rain exposure (125 mm or more rainfall from one day before to one day after the storm's closest approach) and for tornado event-based exposure (Table 3.1). Community-specific exposures to all tropical cyclones for the three continuous metrics considered (distance to the storm track, maximum sustained winds, and cumulative rainfall) are shown in Figure B1.

Across the study communities and study period, Miami, FL, was exposed to the most severe storm wind exposure (Hurricane Andrew; maximum sustained wind speed: 52.1 m/s), while New Orleans, LA, was exposed to the most severe storm rain exposure (Hurricane Katrina; cumulative rain: 196.2 mm from one day before to one day after the day of storm's closest approach) (Figure B1). Storm exposures experienced by a given community over our study period varied depending on the exposure metric considered; while New Orleans, LA, (19 wind exposures) and Cayce, SC, (16 rain exposures) were threatened by the most storm exposures under wind and rain metrics, St. Petersburg, FL, and Orlando, FL, had the most storm exposures (12 exposures) when storm exposure was determined based on distance to the storm track.

Ten most severe tropical cyclone wind exposures and their associated mortality risks

Table 3.2 shows the estimates of storm-associated relative risks of mortality and excess deaths for all-cause and cardiovascular mortality for the ten most severe tropical cyclone wind exposures in the study, both on the day of the storm's closest approach to the community and across the entire storm period from two days before to seven days after the storm's closest approach. Hurricane Andrew's hit of Miami, FL, was the most severe tropical cyclone wind exposure observed in our study (modeled maximum sustained wind speed in Miami during the storm was 52.1 m/s). This storm exposure was associated with an increase in risk of all-cause mortality on the day of the storm (RR = 1.55, 95% confidence interval (CI), 1.12–2.16). Hurricane Katrina's hit of New Orleans, LA, which was the third most severe tropical cyclone exposure in the study in terms of wind (maximum sustained wind was 40.3 m/s), was associated with the largest increased mortality risk among these storms on all-cause mortality (RR = 43.94, 95% CI, 17.16–112.48); this storm also brought severe winds to Miami, FL, (maximum sustained wind: 32.3 m/s) resulting in a large increase in all-cause mortality risk on the day of storm's closest approach in that community, as well (RR = 1.57, 95% CI, 1.02–2.41).

When considering cumulative relative risks across the entire storm period, Hurricane Katrina's hit of New Orleans was also associated with the largest increased risks for all-cause (cumulative RR = 5.77, 95% CI, 4.94–6.73) and cardiovascular mortality (cumulative RR = 2.46, 95% CI, 1.80–3.36) among these storms, translating to 497 and 48 excess deaths, respectively. Substantial increased mortality risks over storm period were also observed in Miami, FL, from exposure to Andrew (cumulative RR = 1.25, 1.14–1.37), Katrina (1.23, 1.11–1.37), and Irene (1.12, 1.02–1.23). In some instances, the risks of cardiovascular mortality remained elevated on several days across the storm period; for example, we estimated 69 excess cardiovascular deaths for the storm period based on the cumulative RR versus 6 on the day of Hurricane

Andrew's closest approach to Miami. The pattern of lag-specific RRs are shows in Figure B2 and B3 (in Appendix B) for these ten most notable tropical cyclone wind exposures.

All tropical cyclones considered and their mortality risks based on all the exposure metrics

Next, we examined the mortality risks associated with all tropical cyclone exposures under each of the tropical cyclone exposure metrics considered. In a few cases, a study community was exposed to two tropical cyclones on a single day based on a given exposure metric. For example, using the most lenient rain-based exposure metric, Kingston, NY, and Newport News, VA, were exposed to both Hurricane Gaston and Tropical Storm Hermine on August 31, 2004. Using the flood-based exposure metric, Kingston, NY, was also exposed to these two tropical cyclones on the same day. In these cases, we modeled the effects of the two storm events as a single exposure day for the study community, since effects of two storm on the same day cannot be separated using our modeling approach. Table 3.1 shows the number of storm exposures under all the exposure metrics investigated.

Under the strictest thresholds of wind- and rain-based exposure metrics (i.e., maximum sustained wind speed > 21 m/s, cumulative rainfall > 125 mm), we found statistically significant increases in risks for all-cause (wind: RR = 1.42, 95% CI, 1.36–1.49; rain: RR = 1.69, 1.60–1.79), cardiovascular (wind: 1.15, 1.06–1.24; rain: 1.30, 1.18–1.44), and accidental mortality (wind: 12.03, 10.87–13.32; rain: 22.53, 20.03–25.35) on the day of the storm's closest approach to the community (lag 0) (Figure 3.2). For those two metrics, patterns in mortality risk across the storm period were similar, with largest associations on the day of storm's closest approach. There was also some evidence that some mortality risks were elevated on the day before and a few days after the storm's closest approach, particularly for accidental mortality, although the associations on these days were much smaller than on the day of the storm's closest approach. The observed associations generally decreased as more lenient thresholds were used to classify a community as exposed based on wind and rain metrics (Figure B5-B8).

In contrast, for the distance-based metric, while no evidence of association was found using the most stringent threshold (distance to storm track < 25 km, Figure B4), associations were observed for some mortality outcomes when the distance threshold was relaxed. Flood- and tornado-based tropical cyclone exposure, as assessed here, showed no association with any of the mortality outcomes considered with the exception of some evidence of an association between flood exposure and elevated risk of respiratory mortality (Figure B4), which was also observed under wind-based exposure (Figure 3.2 and B7). Given the number of statistical tests represented in these supplemental results (Appendix B), some of the statistically significant results may be spurious, particularly for isolated results (e.g., increased risk of respiratory mortality for two higher-lag days based on flood exposure, Figure B4).

We also estimated, for all storm exposures in the study, the cumulative RR of mortality risk throughout the storm period (two days before to seven days after the day of storm's closest approach to the community) (Figure 3.3). For wind-based exposure metric, cumulative risks were consistently elevated during storm periods for all-cause, cardiovascular, and accidental mortality under all thresholds of wind speed considered in determining storm exposure, although the size of the association generally decreased as thresholds become more lenient, particularly for all-cause (cumulative RRs = 1.90, 1.54, 1.38, and 1.33 based on the most to least constrictive thresholds, respectively) and accidental mortality. For the rain-based exposure metric, we observed a large increased risk during storm periods for all-cause, cardiovascular, and accidental mortality, but, with the exception of accidental mortality, this increase was only observed under the strictest threshold of the rain metric considered.

For distance-based exposure, we found evidence of increased risk of all-cause (distance to storm track < 100 km: cumulative RR = 1.15, 1.05–1.25) and accidental mortality (cumulative RR = 4.63, 2.92–7.33) but, interestingly, only when using more lenient thresholds for exposure. Little evidence was found for associations between flood- or tornado-based exposure and mortality risk for the four outcomes considered, with the exception of some evidence of increased risk of respiratory mortality associated with flood-based exposure. Sensitivity analysis showed that, under most exposure metrics investigated, the cumulative risks of all-cause and cardiovascular mortality using the subset of large-population communities (the subset used in our primary analyses for respiratory and accidental mortality outcomes) were consistent with results based on all the study communities (Figure B9).

Finally, we investigated whether the patterns observed when analyzing all tropical cyclone exposures in all exposed communities were dominated by extremely high risks associated with a few of the most severe tropical cyclone exposures, as based on the wind exposure metric. We estimated the RRs based on the subset of all other tropical cyclone exposures, excluding the ten most severe tropical cyclone wind exposures (shown in Table 3.2). When the ten most severe storm exposures were removed from analysis, we observed little evidence of associations between these less severe storm exposures and mortality risk on the day of storm's closest approach (Table B1). However, the cumulative RRs estimated for the entire storm period remained elevated without the most severe storm exposures, though the associations were much lower than when considering all storm exposures (cumulative RRs of all-cause mortality were 1.90, 95% CI, 1.58–2.29, for all tropical cyclone exposures, and 1.18, 95% CI, 0.96–1.45, for these less severe storm exposures).

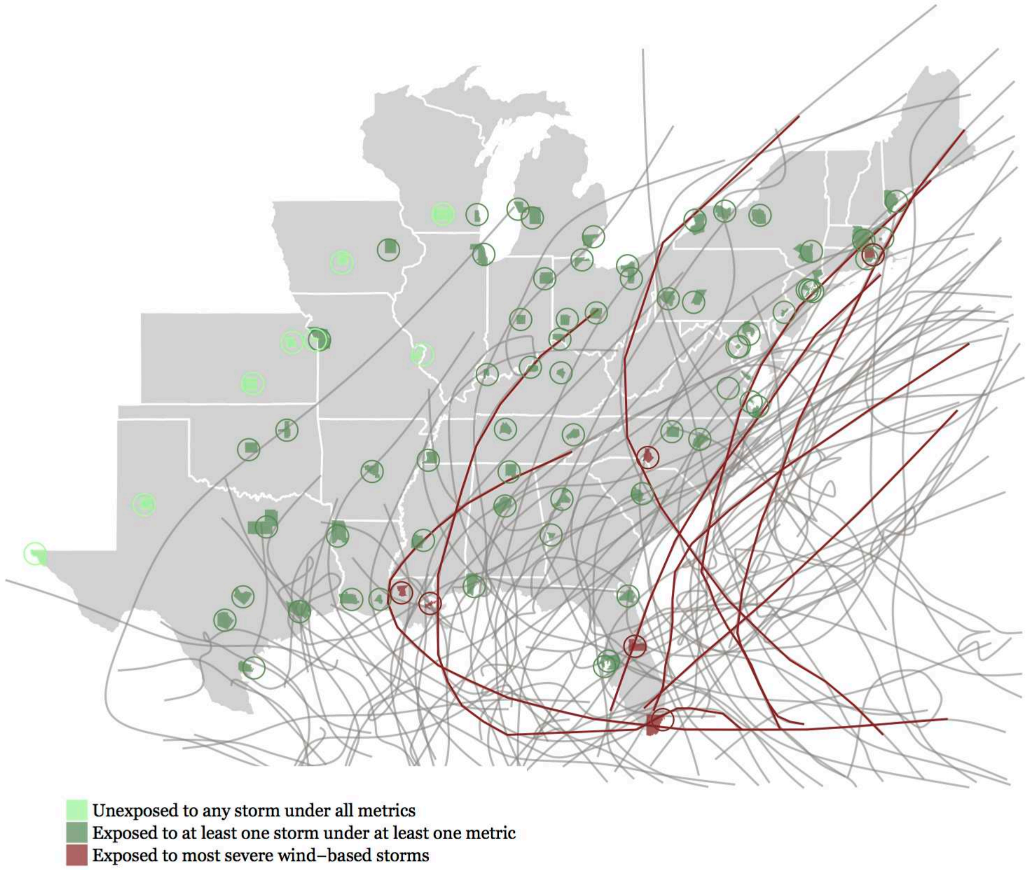

Figure 3.1 Map of study communities (78 total) and storm tracks of all tropical cyclones considered in this study. Storm tracks are shown for all Atlantic-basin tropical cyclones (92 total) that came within 250 km of at least one county in the eastern U.S. between 1988 and 2005. Tracks of ten most notable tropical cyclones exposures, based on the wind-based metric, are shown in red, with the corresponding communities affected shown with red circles. For study communities, each circle shows a community considered in the study, with filled shapes inside the circle showing the county or counties comprising that community.

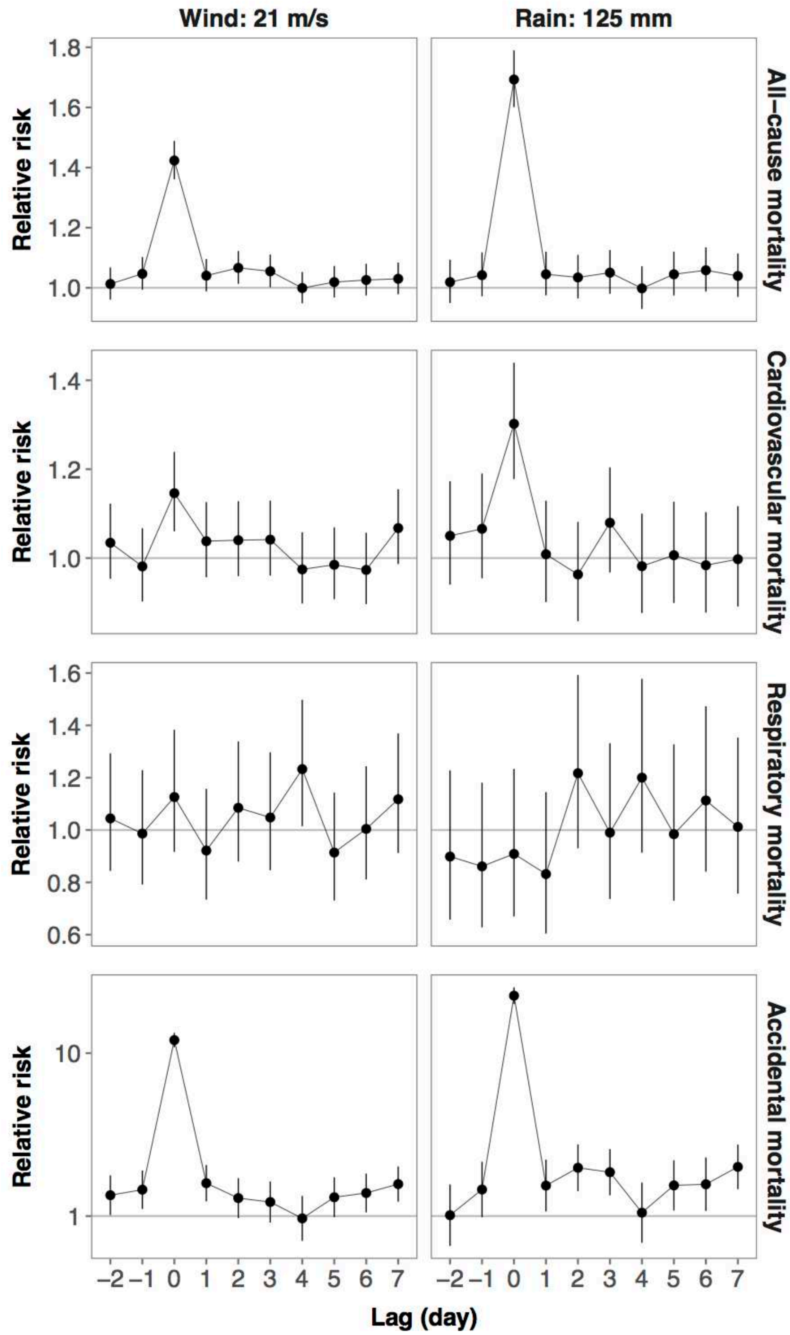

Figure 3.2 Estimates of lag-specific relative risk of mortality on days during storm periods compared to matched days in non-storm periods, across all tropical cyclone exposures for study storms and study communities, based on the strictest thresholds for wind- and rain-based exposure metrics. Lag 0 represents the day of the storm's closest approach to the community, lag -1 the day before the storm's closest approach, lag 1 the day after the storm's closest approach, etc. Models for respiratory and accidental mortality were fit using only communities with population of > 400,000 to prevent model convergence problems, as both of these outcomes are typically less frequent across study communities than cardiovascular and all-cause mortality; results for all-cause and cardiovascular mortality using the same subset of larger-population communities is included in the supplemental material as a sensitivity analysis.

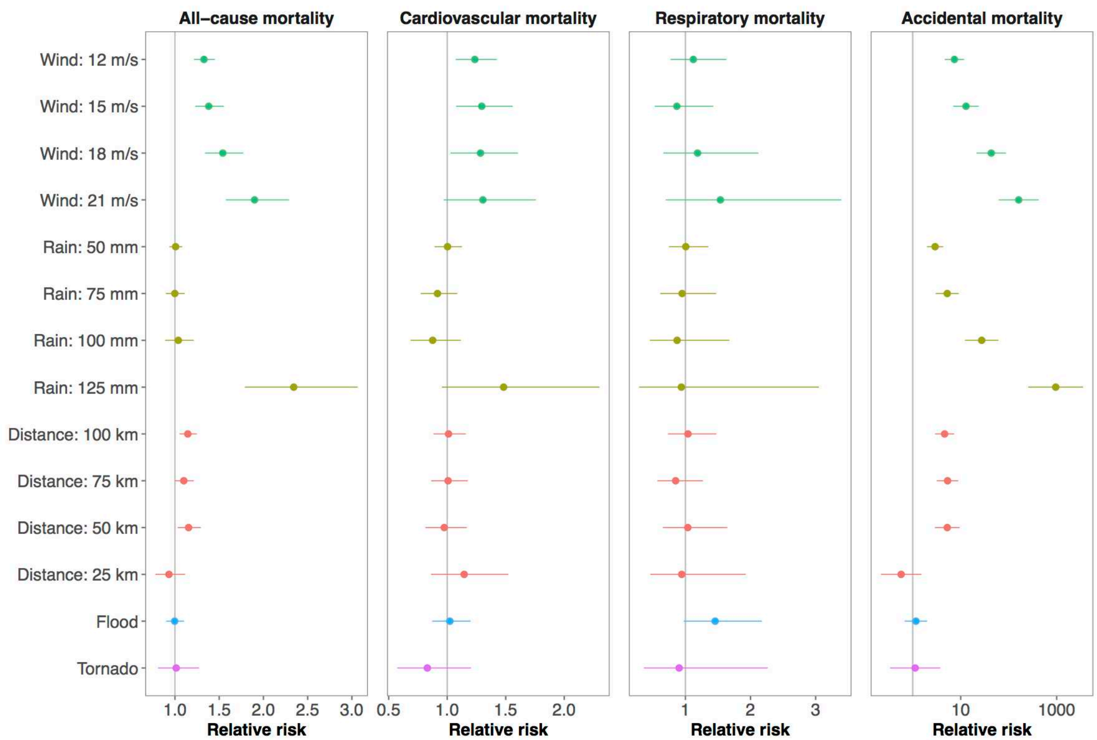

Figure 3.3 Estimates of cumulative relative risk of tropical cyclone exposures on mortality across the full storm period considered (two days before to seven days after the date of storm's closest approach to the community) compared to matched non-storm periods. Color indicates the metric used for defining tropical cyclone exposure (maximum sustained wind speed ['Wind'], cumulative rainfall ['Rain'], distance to storm track ['Distance'], flood event ['Flood'], or tornado event ['Tornado']), with the specific threshold used to identify tropical cyclone exposures based on continuous metrics (wind, rain, and distance) given on the y-axis. Note that x-axis scales differ for each cause of death considered, and a log-10 scale spacing is used for accidental deaths to accommodate the range of estimated relative risks for that outcome.

Table 3.1 Number of storm exposure under each of the exposure metrics investigated. The first number given in each cell is the total number of storm exposures in the study under that exposure metric, where a storm exposure is the combination of a storm hitting a specific study community (i.e., a single storm can cause multiple storm exposures, if it affects multiple study communities). The second number is the total number of study communities with at least one storm exposure under the metric. Number of exposures are shown for both the full collection of study communities and for the subset of study communities with populations greater than 400,000. For continuous exposure measurements (maximum sustained winds, cumulative rainfall, and distance to the storm track), the number of exposures are given for each of the thresholds of exposure considered in the study, from least to most constrictive.

Exposure metric	No. of tropical cyclone exposures [No. of communities]	
	All study communities	Large-population communities*
Maximum sustained winds		
12 m/s	336 [56]	205 [38]
15 m/s	192 [49]	120 [31]
18 m/s	124 [37]	84 [24]
21 m/s	83 [26]	52 [16]
Cumulative rainfall		
50 mm	445 [63]	283 [41]
75 mm	214 [55]	128 [35]
100 mm	104 [37]	61 [23]
125 mm	50 [26]	29 [16]
Distance to storm track		
100 km	347 [68]	218 [45]
75 km	259 [65]	167 [43]
50 km	175 [61]	118 [40]
25 km	79 [44]	57 [29]
Events		
Flood event(s)	180 [51]	131 [35]
Tornado event(s)	53 [22]	35 [14]

*Large-population communities are those with population greater than 400,000.

Table 3.2 Estimates of relative risk of all-cause and cardiovascular mortality, as well as associated excess death estimates, of ten most severe tropical cyclone wind exposures across the study storms and communities. Estimates are included for both the day of the storm's closest approach to the community ('Same-day estimates') and across the period from two days before to seven days after the storm's closest approach

			All-cause mortality		Cardiovascular mortality	
Storm	Community	Wind (m/s)	Relative risk	Excess deaths	Relative risk	Excess deaths
Same-day estimates						
Andrew (1992)	Miami	52.1	1.55 (1.12, 2.16)	22 (7, 34)	1.47 (0.89, 2.42)	9 (-3, 16)
Charley (2004)	Orlando	41.2	0.40 (0.13, 1.23)	-26 (-114, 3)	0.70 (0.12, 4.24)	-2 (-38, 4)
Katrina (2005)	New Orleans	40.3	43.94 (17.16,	543 (524, 551)	38.69 (7.37, 203.21)	65 (58, 67)
Katrina (2005)	Providence	33.5	1.17 (0.60, 2.30)	2 (-9, 8)	1.47 (0.55, 3.98)	2 (-6, 5)
Katrina (2005)	Miami	32.3	1.57 (1.02, 2.41)	20 (1, 32)	1.30 (0.69, 2.43)	5 (-10, 13)
Andrew (1992)	Baton Rouge	31.8	1.58 (0.59, 4.25)	3 (-5, 5)	4.00 (0.73, 21.92)	3 (-1, 4)
Irene (1999)	Miami	31.3	1.13 (0.72, 1.79)	5 (-17, 19)	1.53 (0.76, 3.07)	8 (-7, 15)
Wilma (2005)	Miami	31.0	0.88 (0.60, 1.29)	-6 (-30, 10)	0.95 (0.54, 1.66)	-1 (-18, 9)
Hugo (1989)	Charlotte	30.8	0.80 (0.27, 2.31)	-2 (-16, 3)	2.11 (0.38, 11.66)	2 (-7, 4)
Bertha (1996)	Providence	30.8	1.03 (0.54, 1.94)	0 (-13, 8)	1.43 (0.54, 3.76)	2 (-7, 6)
Cumulative estimates						
Andrew (1992)	Miami	52.1	1.25 (1.14, 1.37)	108 (67, 146)	1.38 (1.20, 1.58)	69 (43, 92)
Charley (2004)	Orlando	41.2	1.09 (0.89, 1.32)	12 (-18, 37)	1.09 (0.78, 1.51)	4 (-15, 18)
Katrina (2005)	New Orleans	40.3	5.77 (4.94, 6.73)	497 (479, 512)	2.46 (1.80, 3.36)	48 (36, 57)
Bob (1991)	Providence	33.5	1.01 (0.83, 1.22)	1 (-25, 23)	1.05 (0.79, 1.39)	3 (-16, 16)
Katrina (2005)	Miami	32.3	1.23 (1.11, 1.37)	95 (49, 136)	1.15 (0.97, 1.36)	25 (-5, 50)
Andrew (1992)	Baton Rouge	31.8	1.03 (0.81, 1.32)	2 (-17, 18)	1.17 (0.82, 1.68)	5 (-8, 14)
Irene (1999)	Miami	31.3	1.12 (1.02, 1.23)	55 (11, 95)	1.17 (1.02, 1.35)	33 (4, 57)
Wilma (2005)	Miami	31.0	0.98 (0.88, 1.09)	-8 (-63, 41)	0.97 (0.82, 1.15)	-7 (-43, 24)
Hugo (1989)	Charlotte	30.8	0.99 (0.78, 1.26)	-1 (-25, 18)	0.98 (0.67, 1.42)	-1 (-17, 10)
Bertha (1996)	Providence	30.8	0.95 (0.79, 1.13)	-8 (-35, 16)	0.91 (0.69, 1.21)	-5 (-25, 10)

5. Discussion

We estimated storm-associated mortality risks by comparing community-wide mortality rates during storm periods with mortality rates in matched unexposed periods, with the aim of estimating the change in mortality risk during the storm compared to if the storm had not hit the community. We found tropical cyclone wind and rain exposures were associated with substantially increased risks of all-cause, accidental, and cardiovascular mortality based on evidence from a large number of communities in the eastern U.S. between 1988 and 2005. Our results suggest that tropical cyclone exposures, especially from very severe wind, may have important impacts on mortality from not only accidental causes, but also from non-accidental causes. Mortality risks were most elevated on the day of the storm's closest approach to a community; however, there was also some evidence of elevated mortality risks on the day before and a few days following the storm's closest approach, especially for accidental mortality. These observed associations between tropical cyclone exposure and community-wide mortality risk seemed to be dominated, however, by extreme risks associated with a few very severe tropical cyclone wind exposures within the study communities and storms, including the exposures of New Orleans, LA, and Miami, FL, to Hurricane Katrina in 2005 and of Miami, FL, to Hurricane Andrew in 1992. Taken together, these findings help deepen the understanding of the community-wide impacts of hurricanes and other tropical cyclones on mortality from accidental and natural causes, providing insights that are complementary to previous findings from traditional surveillance studies of mortality associated with tropical cyclones.

While some studies using traditional surveillance activities have identified a few tropical storm-related cardiovascular deaths (e.g., from heart attacks) (29,31,32,51), studies using the traditional surveillance approach are likely to undercount the number of deaths from non-accidental causes associated with a tropical cyclone because such deaths are common without tropical cyclone exposure and thus are hard to definitively link, on a case-by-case basis, with tropical storm exposure. Here, we estimated greater impacts associated with tropical cyclone exposures for non-accidental mortality than was previously identified for some of our study storms and communities in traditional surveillance studies. For example, during Hurricane Andrew in Dade County, a surveillance study of storm-related deaths identified two cardiovascular deaths—one from an acute myocardial infarct and the other from atherosclerotic heart disease—on the day of the storm, as well as twelve additional storm-related cardiovascular deaths in the two weeks following the storm (29). In contrast, here we estimated an increased risk of all-cause mortality in the same community during the storm that translates to 9 excess cardiovascular deaths on the day when Hurricane Andrew struck Miami and a total of 69 excess deaths during the ten-day storm period (Table 3.2), which was much higher than the recognized storm-related cardiovascular deaths based on traditional surveillance method. Smaller studies of single years or storms have found similar evidence using a community-wide assessment design that tropical storm exposure can have larger impacts on all-cause mortality in affected communities than identified through traditional surveillance studies, and that these impacts can include important impacts from increased risk of cardiovascular deaths. For example, one study of the four 2004 Florida hurricanes estimated more than 600 excess deaths, while about 150 deaths were ascertained based on surveillance (24), and Hurricane Sandy was associated with a 31% increase in 30-day cardiovascular mortality in New Jersey as compared with previous years (52).

Our findings provide evidence of important risks and impacts associated with cardiovascular mortality from tropical cyclone exposures, often in excess of those impacts identified with more traditional methods of generating storm-related fatality tolls. Although the biological mechanisms through which tropical cyclone exposure increases risk of mortality from non-accidental causes are not well understood, there are plausible explanations linking tropical cyclones and cardiovascular and respiratory mortality, such as infrastructure damage and storm-induced stress. First, tropical cyclone hazards (such as heavy rainfall, strong winds, and storm surge) can damage infrastructure, resulting in power outages and damage to hospitals and transportation systems (28,53,54). During tropical cyclones, power outages can result from extreme rainfall or flood damage to underground electrical infrastructure, as well as from strong winds destroying above-ground wires (30). Power outages can impede communication, cause difficulty accessing health care providers, prevent hospitals from functioning normally (creating particularly threatening conditions for patients in Intensive Care Units (13)), and increase exposure to air pollution and temperature extremes (28), all of which can be risk factors of cardiovascular and respiratory death (30,55,56). Transportation damage due to flooding and strong winds from tropical cyclones could also be associated with disruptions in treatment. For example, emergency department visits (ED) on Long Island (NY) dropped significantly on the day of Hurricane Sandy's landfall (57), which may have been due to the storm's effects on transportation limiting access to EDs. Similar results were also observed in two central Florida EDs on the days of three 2004 hurricanes' landfalls (58). During tropical cyclones or other natural disasters, treatment disruptions can result in serious and even fatal health consequences, especially among populations with chronic medical conditions (59). Storm-related infrastructure damages can also be related to indirect pathways of risk for accidental mortality. For example, during the widespread power outage produced by Hurricane Irma, 12 people died of heat stress in a Florida nursing home due to loss of air-conditioning (28), and reported carbon monoxide exposures were significantly increased following Hurricane Sandy (2012) as compared with same days in previous years (60).

Second, stress related to tropical cyclone exposure may contribute to the observed increases in mortality risk from non-accidental causes. Disaster-induced psychological stress has been associated with increased risks of heightened platelet activation and increased risk of acute coronary disease (61,62) and upper respiratory infection (63). Previous literature has extensively explored the interplay of disaster exposure, psychological stress, and cardiovascular disease in the context of earthquakes (64,65); a similar pathway could exist with tropical cyclones. For example, one study found post-traumatic stress disorder related to Hurricane Katrina was an independent risk factor for cardiovascular disease among hypertensive elderly adults in southeastern Louisiana (66), although the timescale at which these associations were explored were longer than the periods surrounding storms that were investigated in our study.

We found that there can be extraordinary impacts on cardiovascular deaths during tropical cyclones with the most intense wind exposures, but once we took out these very severe tropical cyclone wind exposures, there was little evidence that the remaining tropical cyclone exposures, on average, increase the risk of cardiovascular mortality substantially within a community (shown in Table B1). These findings suggest that our estimates of overall death risks across all tropical cyclones could be dominated by those very severe tropical cyclone wind exposures, especially for cardiovascular mortality. As discussed earlier, cardiovascular deaths from tropical cyclones may be associated with infrastructure damage and stress. The physical damage caused by tropical cyclones is strongly associated with the speed of the winds from the storm at a location. For example, one study found the percentage of structural damage associated with Hurricane Andrew increased exponentially with wind speed at wind speeds greater than 45 m/s (48). If infrastructure damage, and stress related with this damage, are particularly important pathways in increasing tropical cyclone-related mortality risks, particularly risks associated with cardiovascular mortality, this could help explain why mortality risks associated with particularly severe tropical cyclone wind exposures seemed to dominate the associations identified in our study.

Consistent with previous studies using the surveillance approach, we also found substantial impacts on accidental mortality from tropical cyclone exposures. Based on the traditional surveillance method, about 2,170 deaths were directly related to tropical cyclones in the U.S. from 1963 to 2012 (7,8). According to the guidelines provided by U.S. CDC about how to ascertain death and complete death certificates following tropical cyclones (9,67), nearly all the deaths classified as directly related to tropical cyclones can be coded as accidental deaths. Based on a community-wide assessment of mortality risks, we estimated a RR of 22.53 (95% CI, 20.03–25.35) for accidental death on the day of storm's closest approach to the community for all tropical cyclones considered and across all the exposed communities, under the strictest threshold of rain-based exposure. For respiratory mortality from tropical cyclones, while an immediately increased risk was not consistently evident in our study, fatal and non-fatal respiratory outcomes have been previously been reported to be associated with some certain tropical cyclone exposures, both in the rapid assessment immediate after tropical cyclones (68) and during the following month (25) or years (69), especially among vulnerable populations like children (70).

There was some evidence that mortality risks were elevated on the day before and a few days after the day of storm's closest approach, in particular for wind and rain tropical cyclone exposures. Similar findings were also seen in earlier studies (11,71); for example, out of 799 Katrina-related deaths with a recorded date of death in Louisiana, seven occurred on the two preceding days and about fifty in the week following the storm, based on surveillance activity (11). Conditions related to pre-storm preparation, evacuation, and post-storm cleanup may all contribute to the increased risk of mortality on the days surrounding the defined storm-exposed day, as evidenced in both preliminary reports (29,31,71) and more thorough studies (11,51,72–74). For example, one of the deaths attributed to Hurricane Charley in Florida was caused by a heart attack suffered while cleaning up after the storm, and several accidental deaths attributed to this storm were related to falls during post-storm cleanup (31). Similarly, following Hurricane Andrew, seven deaths in Dade County that were attributed to the storm were caused by increased physical exertion during post-storm cleanup (29). Further, although evacuations typically reduce people's exposure to tropical cyclone winds, rains, flooding, and tornadoes, evacuation can pose its own risks to health, and increased risk of death among evacuees has indeed been identified in earlier studies (11,29,71). For example, in a recent study of four Florida hurricanes, evacuation was found to substantially increase 90-day probability of death among nursing home residents, as compared with those residing in the same facilities during the same time in non-storm years (72).

Our analyses of community-wide mortality risks from tropical cyclones adds two important insights to results from traditional surveillance. First, the health impacts of tropical cyclones on non-accidental mortality can, in some cases, be much greater than identified in case-by-case surveillance studies. Second, intense wind exposures characterized several of the tropical cyclones with particularly high associated risks of non-accidental mortality in this study. Given that the intensity of tropical cyclones in Atlantic basin may increase under climate change (3,75), and the population density in the tropical cyclone-prone coastal areas has greatly increased and is expected to continue to increase (76), improving understanding of the full-scale health impacts from tropical cyclones and other climate-related disasters is a high priority in climate change and public health research.

References

1. Knutson TR, McBride JL, Chan J, et al. Tropical cyclones and climate change. *Nature Geoscience*. 2010;3(3):157.
2. Knutson TR, Sirutis JJ, Zhao M, et al. Global projections of intense tropical cyclone activity for the late twenty-first century from dynamical downscaling of CMIP5/RCP4.5 scenarios. *Journal of Climate*. 2015;28(18):7203–7224.
3. Bender MA, Knutson TR, Tuleya RE, et al. Modeled impact of anthropogenic warming on the frequency of intense Atlantic hurricanes. *Science*. 2010;327(5964):454–458.
4. Czajkowski J, Simmons K, Sutter D. An analysis of coastal and inland fatalities in landfalling US hurricanes. *Natural Hazards*. 2011;59(3):1513–1531.
5. Jung K, Shavitt S, Viswanathan M, et al. Female hurricanes are deadlier than male hurricanes. *Proceedings of the National Academy of Sciences*. 2014;111(24):8782–8787.
6. Rappaport EN. Loss of life in the United States associated with recent Atlantic tropical cyclones. *Bulletin of the American Meteorological Society*. 2000;81(9):2065–2073.
7. Rappaport EN. Fatalities in the United States from Atlantic tropical cyclones: New data and interpretation. *Bulletin of the American Meteorological Society*. 2014;95(3):341–346.
8. Rappaport EN, Blanchard BW. Fatalities in the United States indirectly associated with Atlantic tropical cyclones. *Bulletin of the American Meteorological Society*. 2016;97(7):1139–1148.
9. Centers for Disease Control and Prevention. A reference guide for certification of deaths in the event of a natural, human-induced, or chemical/radiological disaster. *NVSS: National Vital Statistics System* [electronic article]. 2017;(1). (https://www.cdc.gov/nchs/nvss/reporting-guidance.htm)
10. Combs DL, Parrish RG, McNABB SJ, et al. Deaths related to Hurricane Andrew in Florida and Louisiana, 1992. *International Journal of Epidemiology*. 1996;25(3):537–544.
11. Brunkard J, Namulanda G, Ratard R. Hurricane Katrina deaths, Louisiana, 2005. *Disaster Medicine and Public Health Preparedness*. 2008;2(4):215–223.
12. Naumann RB, Dellinger AM, Kresnow M-j. Driving self-restriction in high-risk conditions: How do older drivers compare to others? *Journal of Safety Research*. 2011;42(1):67–71.
13. Gray BH, Hebert K. Hospitals in Hurricane Katrina: Challenges facing custodial institutions in a disaster. *Journal of Health Care for the Poor and Underserved*. 2007;18(2):283–298.
14. Aumentan a 64 muertes certificadas por maría. 2017;(https://www.telemundopr.com/noticias/destacados/Aumentan-a-64-las-muertes-por-el-huracan-Maria-463005263.html)
15. Santos-Lozada AR, Howard JT. Use of death counts from vital statistics to calculate excess deaths in Puerto Rico following Hurricane Maria. *Journal of the American Medical Association*. 2018;
16. Kishore N, Marques D, Mahmud A, et al. Mortality in Puerto Rico after Hurricane Maria. *New England Journal of Medicine* [electronic article]. 2018;(https://doi.org/10.1056/NEJMsa1803972)
17. Santos-Burgoa C, Goldman A, Andrade E, et al. Acertainment of the estimated excess mortality from Hurricane Maria in Puerto Rico. 2018;
18. Robles F, Davis K, Almukhtar S. Official Toll in Puerto Rico: 64. Actual Deaths May Be 1,052. 2017;(https://www.nytimes.com/interactive/2017/12/08/us/puerto-rico-hurricane-maria-death-toll.html)
19. Rivera R, Rolke W. Estimating the death toll of Hurricane Maria. *Significance*. 2018;15(1):8–9.
20. Puerto Rico increases Hurricane Maria death toll to 2,975. 2018;(https://www.bbc.com/news/world-us-canada-45338080?intlink_from_url=&link_location=live-reporting-story)
21. Bobb JF, Obermeyer Z, Wang Y, et al. Cause-specific risk of hospital admission related to extreme heat in older adults. *Journal of the American Medical Association*. 2014;312(24):2659–2667.
22. Gronlund CJ, Zanobetti A, Schwartz JD, et al. Heat, heat waves, and hospital admissions among the elderly in the United States, 1992–2006. *Environmental Health Perspectives*. 2014;122(11):1187.

23. Gasparrini A, Guo Y, Hashizume M, et al. Temporal variation in heat–mortality associations: A multicountry study. *Environmental Health Perspectives*. 2015;123(11):1200.
24. McKinney N, Houser C, Meyer-Arendt K. Direct and indirect mortality in Florida during the 2004 hurricane season. *International Journal of Biometeorology*. 2011;55(4):533–546.
25. Kim S, Kulkarni PA, Rajan M, et al. Hurricane Sandy (New Jersey): Mortality rates in the following month and quarter. *American Journal of Public Health*. 2017;107(8):1304–1307.
26. Kelman J, Finne K, Bogdanov A, et al. Dialysis care and death following Hurricane Sandy. *American Journal of Kidney Diseases*. 2015;65(1):109–115.
27. Sanchez R. Workers laid off at now-closed Florida nursing home where 12 died. 2017;(https://www.cnn.com/2017/10/07/us/florida-hollywood-nursing-home/index.html)
28. Shultz JM, Galea S. Preparing for the next Harvey, Irma, or Maria—addressing research gaps. *New England Journal of Medicine*. 2017;377(19):1804–1806.
29. Lew EO, Wetli CV. Mortality from Hurricane Andrew. *Journal of Forensic Science*. 1996;41(3):449–452.
30. Lane K, Charles-Guzman K, Wheeler K, et al. Health effects of coastal storms and flooding in urban areas: A review and vulnerability assessment. *Journal of Environmental and Public Health*. 2013;2013.
31. Centers for Disease Control and Prevention. Preliminary medical examiner reports of mortality associated with Hurricane Charley–Florida, 2004. *Morbidity and Mortality Weekly Report*. 2004;53(36):835.
32. Centers for Disease Control and Prevention. Preliminary report: Medical examiner reports of deaths associated with Hurricane Andrew–Florida, August 1992. *Morbidity and Mortality Weekly Report*. 1992;41(35):641–644.
33. Combs DL, Quenemoen LE, Parrish RG, et al. Assessing disaster-attributed mortality: Development and application of a definition and classification matrix. *International Journal of Epidemiology*. 1999;28(6):1124–1129.
34. Bell ML, McDermott A, Zeger SL, et al. Ozone and short-term mortality in 95 US urban communities, 1987–2000. *Journal of the American Medical Association*. 2004;292(19):2372–2378.
35. Landsea CW, Franklin JL. Atlantic hurricane database uncertainty and presentation of a new database format. *Monthly Weather Review*. 2013;141:3576–3592.
36. Anderson B, Yan M, Ferreri J, et al. hurricaneexposure: Explore and map county-level hurricane exposure in the United States. 2017.(https://cran.r-project.org/package=hurricaneexposure)
37. U.S. 2010 Decennial Census. (https://www2.census.gov/geo/docs/reference/cenpop2010/county/CenPop2010_Mean_CO.txt)
38. Rui H, Mocko D. README Document for North America Land Data Assimilation System Phase 2 (NLDAS-2) Products. *Greenbelt, Maryland*. 2014;
39. Al-Hamdan MZ, Crosson WL, Economou SA, et al. Environmental public health applications using remotely sensed data. *Geocarto International*. 2014;29(1):85–98.
40. Willoughby H, Darling R, Rahn M. Parametric representation of the primary hurricane vortex. Part II: A new family of sectionally continuous profiles. *Monthly Weather Review*. 2006;134(4):1102–1120.
41. Anderson B, Schumacher A, Guikema S, et al. Stormwindmodel: Model tropical cyclone wind speeds. 2017.(https://CRAN.R-project.org/package=stormwindmodel)
42. NOAA, National Centers for Environmental Information. Storm Events Database. 2018;(https://www.ncdc.noaa.gov/stormevents/)
43. Anderson B, Schumacher A, Crosson W, et al. hurricaneexposuredata: Data characterizing exposure to hurricanes in United States counties. 2017.(https://github.com/geanders/hurricaneexposuredata)
44. Liu JC, Wilson A, Mickley LJ, et al. Wildfire-specific fine particulate matter and risk of hospital admissions in urban and rural counties. *Epidemiology*. 2017;28(1):77–85.
45. Gasparrini A. Modeling exposure-lag-response associations with distributed lag non-linear models. *Statistics in Medicine*. 2014;33(5):881–899.

46. Costa AF, Hoek G, Brunekreef B, et al. Air pollution and deaths among elderly residents of Sao Paulo, Brazil: An analysis of mortality displacement. *Environmental Health Perspectives*. 2016;125(3):349–354.
47. Schott T, Landsea C, Hafele G, et al. The Saffir-Simpson hurricane wind scale. *NOAA/National Weather Service [Internet]*. 2012;1–4.
48. Powell MD, Houston SH, Ares I. Real-time damage assessment in hurricanes. In: *Preprints, 21st Conf. on Hurricanes and Tropical Meteorology, Miami, FL, Amer. Meteor. Soc*. 1995:500–502.
49. Mallin MA, Corbett CA. How hurricane attributes determine the extent of environmental effects: Multiple hurricanes and different coastal systems. *Estuaries and Coasts*. 2006;29(6):1046–1061.
50. Steenland K, Armstrong B. An overview of methods for calculating the burden of disease due to specific risk factors. *Epidemiology*. 2006;17(5):512–519.
51. Philen RM, Combs DL, Miller L, et al. Hurricane Hugo-related deaths: South Carolina and Puerto Rico, 1989. *Disasters*. 1992;16(1):53–59.
52. Swerdel JN, Janevic TM, Cosgrove NM, et al. The effect of hurricane sandy on cardiovascular events in New Jersey. *Journal of the American Heart Association*. 2014;3(6):e001354.
53. Ofri D. The storm and the aftermath. *New England Journal of Medicine*. 2012;367(24):2265–2267.
54. Halverson JB. Second wind: The deadly and destructive inland phase of east coast hurricanes. *Weatherwise*. 2015;68(2):20–27.
55. Klinger C, Owen Landeg VM. Power outages, extreme events and health: A systematic review of the literature from 2011–2012. *PLoS Currents*. 2014;6.
56. Anderson GB, Bell ML. Lights out: Impact of the August 2003 power outage on mortality in New York, NY. *Epidemiology (Cambridge, Mass.)*. 2012;23(2):189.
57. Kim H, Schwartz RM, Hirsch J, et al. Effect of Hurricane Sandy on Long Island emergency departments visits. *Disaster Medicine and Public Health Preparedness*. 2016;10(3):344–350.
58. Platz E, Cooper HP, Silvestri S, et al. The impact of a series of hurricanes on the visits to two central Florida emergency departments. *The Journal of Emergency Medicine*. 2007;33(1):39–46.
59. Jhung MA, Shehab N, Rohr-Allegrini C, et al. Chronic disease and disasters: Medication demands of Hurricane Katrina evacuees. *American Journal of Preventive Medicine*. 2007;33(3):207–210.
60. Chen B, Shawn L, Connors N, et al. Carbon monoxide exposures in New York City following Hurricane Sandy in 2012. *Clinical Toxicology*. 2013;51(9):879–885.
61. Strike PC, Magid K, Whitehead DL, et al. Pathophysiological processes underlying emotional triggering of acute cardiac events. *Proceedings of the National Academy of Sciences*. 2006;103(11):4322–4327.
62. Bhattacharyya MR, Steptoe A. Emotional triggers of acute coronary syndromes: Strength of evidence, biological processes, and clinical implications. *Progress in Cardiovascular Diseases*. 2007;49(5):353–365.
63. Pedersen A, Zachariae R, Bovbjerg DH. Influence of psychological stress on upper respiratory infection—a meta-analysis of prospective studies. *Psychosomatic Medicine*. 2010;72(8):823–832.
64. Leor J, Poole WK, Kloner RA. Sudden cardiac death triggered by an earthquake. *New England Journal of Medicine*. 1996;334(7):413–419.
65. Dimsdale JE. Psychological stress and cardiovascular disease. *Journal of the American College of Cardiology*. 2008;51(13):1237–1246.
66. Lenane Z, Peacock E, Krousel-Wood M. 2115: Post-traumatic stress disorder associated with Hurricane Katrina predicts cardiovascular disease events among elderly adults. *Journal of Clinical and Translational Science*. 2017;1(S1):24–24.
67. Centers for Disease Control and Prevention. Completion of death certificates in the aftermath of a hurricane. 2017;(https://www.cdc.gov/nchs/data/dvs/hurricane_certification.pdf)

68. Bayleyegn T, Wolkin A, Oberst K, et al. Rapid assessment of the needs and health status in Santa Rosa and Escambia counties, Florida, after Hurricane Ivan, September 2004. *Disaster Management & Response*. 2006;4(1):12–18.
69. Rando RJ, Lefante JJ, Freyder LM, et al. Respiratory health effects associated with restoration work in post-Hurricane Katrina New Orleans. *Journal of Environmental and Public Health*. 2012;2012.
70. Rath B, Young EA, Harris A, et al. Adverse respiratory symptoms and environmental exposures among children and adolescents following Hurricane Katrina. *Public Health Reports*. 2011;126(6):853–860.
71. Centers for Disease Control and Prevention. Deaths associated with Hurricane Sandy-October–November 2012. *MMWR. Morbidity and Mortality Weekly Report*. 2013;62(20):393.
72. Dosa D, Hyer K, Thomas K, et al. To evacuate or shelter in place: Implications of universal hurricane evacuation policies on nursing home residents. *Journal of the American Medical Directors Association*. 2012;13(2):190–e1.
73. Diakakis M, Deligiannakis G, Katsetsiadou K, et al. Hurricane Sandy mortality in the Caribbean and continental North America. *Disaster Prevention and Management*. 2015;24(1):132–148.
74. Ragan P, Schulte J, Nelson SJ, et al. Mortality surveillance: 2004 to 2005 Florida hurricane-related deaths. *The American Journal of Forensic Medicine and Pathology*. 2008;29(2):148–153.
75. Sobel AH, Camargo SJ, Hall TM, et al. Human influence on tropical cyclone intensity. *Science*. 2016;353(6296):242–246.
76. Crossett K, Ache B, Pacheco P, et al. National coastal population report, population trends from 1970 to 2020. National Oceanic and Atmospheric Administration, Department of Commerce/US Census Bureau; 2014.(https://aamboceanservice.blob.core.windows.net/oceanservice-prod/facts/coastal-population-report.pdf)

Chapter 4: Tropical cyclones-associated risks of emergency Medicare hospital admission for cardiorespiratory diseases in 175 U.S. counties, 1999–2010

1. Chapter overview

While the risk of injury during tropical cyclones has been well characterized based on traditional surveillance activities, the risk of other types of morbidity from exposure to tropical cyclones has seldom been investigated. Further, the elderly (typically defined as adults aged 65 and older) are generally disproportionately affected by disasters due to functional limitations, although research in this regard is also scarce. To provide evidence on health impacts associated with tropical cyclones among the elderly, we analyzed the county-wide associations between tropical cyclones and emergency hospital admissions in the Medicare population. To measure storm exposure, we separately considered five metrics: distance to storm track; cumulative rainfall; maximum sustained wind speed; flooding; and tornadoes. We used Medicare claims made between January 1, 1999 and December 31, 2010 for 180 eastern United States (U.S.) counties and estimated how emergency hospital admissions among the county Medicare beneficiaries differed during tropical cyclone exposures compared to what would have been expected had the storms not occurred We used a matched analysis to compare health risks on storm-exposed days versus similar unexposed days within each county. For each combination of exposure metric and disease outcome, we estimated storm-associated health risks for a window from two days before to seven days after the day of storm's closest approach. Over our study period (1999–2010), 74 Atlantic Basin tropical cyclones were considered based on U.S. landfall or close approach, with 175 out of 180 counties exposed to at least one storm based on at least one exposure metric. Among Medicare beneficiaries, the risks of storms on cardiovascular hospitalizations generally decreased on the day of storm's closest approach, followed by a significant increase on the following days, with the largest increase often found on day two (e.g., when measuring exposure as storm-related maximum sustained wind > 21 m/s at the county's population mean center: RR at lag 0 is 0.93 [95% CI, 0.88–0.98]; RR at lag 1 is 1.00 [95% CI, 0.96–1.05]; and RR at lag 2 is 1.11 [95% CI, 1.06–1.17]). Risks for respiratory disease hospitalizations, in most cases, increased on the day of storm's closest approach, with the largest increase often on the following two days. Cumulative risks of respiratory hospitalizations were increased under all storm exposure metrics considered, for all storms and across all exposed counties; these risks remained significantly elevated (RR = 2.22, 95% CI, 1.53–3.21) even when the ten most severe wind-based storm events were excluded from analysis. Through an examination of the county-wide storm-associated risks on emergency hospitalizations among a large population aged 65 and older, our findings add two important results to the limited literature on health impacts from exposure to tropical cyclones: first, the impact on emergency hospital admissions due to non-injury morbidity (investigated for cardiovascular and respiratory diseases) from exposure to tropical cyclones can increase substantially during storm exposure periods; and second, tropical cyclones with most intense wind exposures may be particularly important in identifying high-risk storms associated with respiratory disease hospitalization among the elderly.

2. Introduction

Tropical cyclones pose a growing threat to human health in the United States. With continuing climate change, the intensity of tropical cyclones, and their associated rainfall rates, are projected to increase in the Atlantic basin in coming decades (1). From 1995 to 2005, about 20% of adults aged 65 and older lived in a county with at least one tropical cyclone exposure (2), making it particularly important to improve our understanding of the potential impacts of these disasters among the elderly. In the United States (U.S.), the percentage of the population aged 65 and older has been increased and is expected continue to increase in the coming decades, with projections anticipating the percentage of Americans in this age group increasing from 15% in 2014 to 24% in 2060 (3). Many of the elderly have functional limitations or other conditions (e.g., vision/hearing impairments, chronic medical conditions) that compromise their ability to stay safe during disasters (4). Given these unique health challenges faced by the elderly, they are at a particularly high risk of disaster related morbidity and mortality. For example, almost half of all deaths in the official New Jersey death toll for Hurricane Sandy (49 out of 106) occurred among people over 65 years old, based on disaster surveillance (5). Similarly, out of the 12 people who died from cardiovascular causes during the two weeks following Hurricane Andrew in Miami-Dade county, 8 were elderly (6). In spite of a growing interest in investigating how natural disasters affect human health (7) and a wide recognition that the elderly are disproportionately affected by disasters (8), there are still few studies specifically examining the health impacts on the elder population from natural disasters, including tropical cyclones (9).

There is much less known about the association between tropical cyclones and non-fatal chronic disease risks than about tropical cyclones' effects on fatalities or injuries, as post-disaster surveillance in the U.S. usually focuses on estimating the toll of fatalities and injuries, with some investigation of infectious disease risks for some disasters (10). Based on a few surveys exploring non-fatal chronic disease outcomes associated with tropical cyclones, especially following Hurricane Katrina, the majority of non-injury-related health care visits during and after storms are due to chronic disease and related conditions, such as hypertension, cardiovascular complaints, and respiratory problems (12). Although an association between tropical cyclones and health care utilizations was observed in these previous studies, literature in this area is still scarce and subject to a number of limitations. First, most studies to investigate the association between tropical cyclones and non-fatal chronic health effects to date have been limited to single-storm studies (15), especially studies focusing on Hurricane Katrina (12) and Hurricane Sandy (16). Second, most studies that have investigated the change in the overall hospital admissions during tropical cyclones (19); there have been few studies on health care utilizations due to some common diseases, even though there are reasons to believe that tropical cyclones may increase the risk of some common diseases like cardiovascular and respiratory disease (21), particularly among the elderly (16). Finally, few studies have provided views of how the health risks associated with tropical cyclones evolve over the period from before the storm, as communities prepare and evacuate, to the day of the storm, then through the post-storm period. Instead, most previous studies have assessed the cumulative health effect of tropical cyclone exposure throughout a two-week or one-month storm period as compared with pre- or post-storm periods (16). Given that the health risks associated with tropical cyclones likely vary substantially throughout this storm period, understanding the evolution of patterns in health care utilization throughout the tropical cyclone period is critical for preparedness and response.

To address research gaps in understanding the risks of non-fatal chronic health outcomes associated with tropical cyclone exposure among the elderly, we examined the associations between tropical cyclone exposures and emergency hospital admissions for cardiovascular and respiratory diseases in the Medicare population in the eastern U.S. from 1999 to 2010. To our knowledge, this is the largest study to date in exploring the patterns in emergency hospitalizations during tropical cyclones.

3. Methods

Data

Tropical cyclones. We identified all tropical cyclones that passed within 250 kilometers of at least one eastern U.S. county during the study period (1988–2005), using the National Hurricane Center's revised Atlantic hurricane database (HURDAT2) (26). For each storm, we then measured county-level storm exposure for all counties based on five metrics: distance to the storm track, cumulative rainfall (from one day before the storm's closest approach to one day after), maximum sustained wind speed modeled at the county's population mean center, occurrence of one or more flood events, and occurrence of one or more tornadoes. Specific details for the exposure assessment based on each of these exposures is included in the Methods section in Chapter 3. For the three continuous exposure metrics (distance to storm track, cumulative rainfall, and maximum sustained wind speed), we considered several different thresholds for classifying a county as exposed based on that metric, to allow us to explore the influence of these threshold choices on hospitalization risk estimates. For all tropical storm exposure assessment, we conducted this exposure classification using the R packages *"hurricaneexposure"* (27) and *"hurricaneexposuredata"* (28).

Study population. We obtained daily counts of emergency hospital admissions for cardiovascular and respiratory disease, based on fee-for-service Medicare claims made between January 1, 1999, and

December 31, 2010, for beneficiaries aged 65 years or older residing in one of 180 study counties in eastern half of the U.S. (Figure 4.1). This Medicare population has also been investigated in previous studies to examine health effects of other ambient environmental exposures, including air pollution (29) and heat waves (30). Cause of disease was classified based on the International Classification of Diseases, ninth revision (ICD-9): cardiovascular disease admissions covered ICD-9 codes 390–398 and respiratory admissions covered ICD-9 codes 464–466, 480–487, and 490–492.

Statistical analysis

We applied the same definition of *storm exposure* as in Chapter 3: a *storm exposure* was defined as the occurrence of a storm bringing conditions to a study community that met one of the storm exposure definitions, based on either distance to the storm track, maximum sustained winds, cumulative rainfall, flooding, or tornadoes. Therefore, a storm could create multiple exposures within our study (if it brought these conditions to multiple study communities), and a study community could experience multiple exposures across the study period, from multiple storms.

Matching. We used a matched-analysis approach, as used in the Chapter 3, to examine the change in emergency hospital admissions during tropical cyclones exposure periods versus matched non-storm periods. We first identified any storm-exposed days for each of the study counties, under each storm exposure metric considered. Study counties with no storm exposure days under any metric were excluded from further analysis. Within each county with one or more storm-exposed days, we then matched each identified storm day to ten non-storm days, matching by seasonality. These ten non-storm days were randomly selected from a pool of candidate non-storm days for the county which were: 1) in a different year; 2) within a seven-day window of the storm day's day of the year (to match for time of year); 3) not within a three-day window of a different storm day for the county; and 4) not in the two-week period starting on September 11, 2001. For each storm day and its ten matched non-storm days, we pulled the series of days from two days before to seven days after these days, to allow us to investigate the association between storm exposure and hospital admissions for a period surrounding the date of a storm's closest approach to a county. For days in the storm period, the day's lag day was set as the amount of time between that day and the day of the storm's closest approach (e.g., if the storm's closest approach was August 31, 2004, then August 29, 2004 was identified as the lag -2 exposure day for that storm).

Association between all tropical cyclone exposures and hospital admissions. We first estimated the overall association across all tropical cyclones over our study period and all exposed study counties. We fit the following generalized linear mixed-effect model to the matched multi-county data, separately for each combination of exposure metric and disease outcome:

$$\log[E(Y_t^c)] = \log(n^c) + \alpha + \alpha^c + \sum_{l=-2}^{7} \beta_l x_{t+l}^c + \boldsymbol{\delta} Year_t + \boldsymbol{\gamma} DOW_t \tag{4.1}$$

where:

- Y_t^c is the number of emergency hospital admissions in Medicare population on day *t* for county *c*;
- n_t^c is the total number of Medicare beneficiaries residing in county *c* on day *t* who were not already hospitalized, included as an offset term to capture the variation in the number of potential hospitalizations on each study day;
- α is the model intercept;
- α^c are random intercepts for each study county, assumed to follow a normal distribution with a mean of 0 and variance of σ^2 (i.e., $\alpha^c \sim \mathrm{N}(0, \sigma^2)$);
- $\sum_{l=-2}^{7} \beta_l x_{t+l}^c$ is an unconstrained distributed lag function of storm exposure variable *x*. β_l is the coefficient estimating the association between tropical cyclone exposure and hospital admission at lag *l* from day *t*, the day of the storm's closest approach to study county *c*. x_{t+l}^c is the indicator variable representing whether a given day at lag *l* from day *t* for county *c* is part of an exposed storm period or part of a matched unexposed period.
- $Year_t$ is an indicator variable of year on day *t*, with $\boldsymbol{\delta}$ as a vector of coefficients for $Year$;

- DOW_t is an indicator variable of day of week on day *t*, with $\boldsymbol{\gamma}$ as a vector of coefficients for DOW.

For each definition of storm exposure, we estimated both lag-specific and cumulative relative risks (RRs), as compared with matched non-storm periods. The lag-specific RRs on each day in the storm period were calculated as $exp(\hat{\beta}_l)$, based on the values of $\hat{\beta}_l$ estimated for eq. 4.1. The cumulative RRs estimate the cumulative risks for hospital admission across the entire storm exposure period, from two days before to seven days after the day of the storm's closest approach, compared to matched periods without storm exposure. The cumulative RRs were calculated as $exp(\sum_{l=-2}^{7}\hat{\beta}_l)$, based on the values of $\hat{\beta}_l$ estimated for eq. 4.1 (31).

Associations between the ten most severe tropical cyclone wind exposures and hospital admissions. To investigate if the overall estimated associations between tropical cyclone exposures and hospital admissions were driven by the few most severe tropical cyclone exposures, we also estimated the storm-specific effects on hospital admissions from exposure to the ten most severe tropical cyclone wind exposures, as well as the average associations between hospitalizations and all other tropical cyclone exposures excluding these ten most severe wind exposures. To ensure adequate statistical power in this subgroup analysis, we limited our analysis to the study counties with > 50,000 Medicare beneficiaries on the day of storm's closest approach to the county.

For each of the top ten tropical cyclone wind exposures, to estimate the RR on the day of storm's closest approach to the county, we applied the following overdispersed Poisson model to the matched single-county, single-storm data:

$$\log[E(Y_t)] = \log(n_t) + \alpha + \beta_t x_t + \boldsymbol{\gamma} DOW_t + \delta Year_t \tag{4.2}$$

where Y_t is the hospital admission count on day *t*; n_t is the total number of unhospitalized Medicare beneficiaries in the county on day *t*; x_t is an indicator variable denoting whether the day *t* is a storm-exposed day or matched unexposed day; DOW_t is an indicator variable of day of week and $\boldsymbol{\gamma}$ is a vector of coefficients for day of week; and $Year_t$ is included as a linear variable to adjust for the long-term linear trend in hospital admissions over time, with δ as the coefficient for year. The value of $\hat{\beta}$ estimated from eq. 4.2 was used to calculated the RR for a certain storm in the affected county on the day of storm's closest approach to the county.

To estimate the cumulative RRs of the most severe tropical cyclone wind exposures, over the entire storm period, we first calculated from the multi-county time series data a total count of hospital admission for the ten-day storm exposure period (i.e., two days before to seven days after the storm's closest approach to the county), as well as for the same period for each matched unexposed day. Since each storm-exposed day was matched to ten unexposed days, the transformed data contained eleven observations for each of these ten most severe tropical cyclone wind exposures. To this data we applied the following overdispersed Poisson model, separately for each of the ten most severe tropical cyclone wind exposures:

$$\log[E(Y_T)] = \log(n_T) + \alpha + \beta_T x_T + \delta Year_T \quad (4.3)$$

where Y_T is the total count of hospital admissions for the storm period; n_T is the average of daily number of hospitalized Medicare beneficiaries in the county over the ten-day storm period; x_T is an indicator variable of storm exposure, with $x_T = 1$ denoting storm-exposed period and $x_T = 0$ the matched unexposed period, with β_T the coefficient of storm exposure during the period; and $Year_T$ is a linear term for year to adjust for the long-term linear trend in hospital admission over time, with δ the coefficient for year.

Finally, we investigated the influence of the ten most severe tropical cyclone wind exposures on the overall estimated associations between tropical cyclones and hospital admissions for all the storms and across all the exposed counties. We fit eq. 4.1 to all other identified storm exposures (excluding the ten most severe wind exposures) across all study counties with Medicare beneficiaries > 50,000 on the day of storm's closest approach to the county. For this analysis, we excluded days within the ten most severe wind exposures from the pool of candidate unexposed matching days.

4. Results

Over the study period (1999–2010), 74 tropical cyclones passed within 250 kilometers of at least one eastern U.S. county and were considered as study storms. Out of the 180 study counties in the eastern half of U.S., 175 counties were exposed to at least one of these storms based on at least one exposure metric (Figure 4.1). The number of exposed counties and storm exposures differed greatly across the five exposure metrics considered (Table 4.1). For all tropical cyclones and across all the exposed counties, the emergency hospital admissions among the Medicare population due to cardiovascular disease and respiratory disease were generally higher during the storm-exposed periods compared with matched unexposed periods (Table 4.1). Under flood-based exposure, three counties (Oneida County, NY; Broome County, NY; and Lackawanna County, PA) were exposed to two storms (Hurricane Gaston and Tropical Storm Hermine) on the same day (August 31, 2004). Since our modeling approach cannot distinguish the effects of two storms on the same day, we modeled the effects of the two storm events as a single exposure day for the three counties.

Under most of the tropical cyclone exposure metrics we considered, tropical cyclone exposure was associated with decreased risks for cardiovascular disease hospitalizations (wind > 21 m/s: RR at lag0 is 0.93, 95% CI, 0.88–0.98) among Medicare beneficiaries on the day of storm's closest approach, compared with risks on matched non-storm days (Figure 4.2 and C6). Following the day of the storm's closest approach, there is evidence that the RR for cardiovascular disease hospitalizations then increased for a few days, with the largest increased risk typically on the second day following the day of storm's closest approach (e.g., wind > 21 m/s: RR at lag 1 is 1.00 [95% CI, 0.96–1.05]; RR at lag 2 is 1.11 [95% CI, 1.06–1.17]; and RR at lag 3 is 1.08 [95% CI, 1.03–1.13]). In a few cases, especially for severe tropical cyclone wind exposures, risks of cardiovascular disease remained elevated for several days following the storm's closest approach. Risks for respiratory disease admissions increased on the day of the storm's closest approach and, like cardiovascular hospitalization risks, also remained elevated for several days after, with this pattern particularly clear when tropical cyclone exposure was assessed based on wind, rain, and distance metrics. For respiratory hospitalizations, there was also some evidence that risk was elevated the two days before the storm's closest approach.

Next, we estimated the cumulative RR of emergency hospitalization across the storm period (two days before to seven days after the day of storm's closest approach to the county) compared with the matched non-storm periods (Figure 4.3). During the storm period, the cumulative RRs for respiratory disease increased under all exposure metrics considered (Figure 4.3). Based on wind and rain exposure metrics, the cumulative RR for respiratory disease admissions steadily increased as we made the threshold for defining tropical cyclone exposure stricter (i.e., increased the wind speed threshold or rainfall threshold). For example, under wind-based exposure, the estimated cumulative RRs for respiratory disease admissions were 1.66 (95% CI, 1.44–1.91), 2.22 (1.85–2.67), 2.99 (2.41–3.72), and 4.28 (3.22–5.69) with a more constrictive threshold. For cardiovascular disease admissions, increased risks were mainly identified under the wind-based exposures compared with other metrics (e.g., wind > 21 m/s: cumulative RR is 1.36 [95%CI, 1.16–1.60]), with little evidence of an association between cumulative hospitalization risks over this storm period and tropical cyclone exposure under several of the exposure metrics (Figure 4.3). A noticeable increase in cardiovascular disease hospitalizations was also found using the strictest threshold of distance-based metric (cumulative RR is 1.14 [95% CI, 0.98–1.34]), although statistical significance was not met (Figure 4.3).

We further estimated the risks of ten most severe tropical cyclone wind exposures for counties with > 50,000 Medicare beneficiaries on the day of storm's closest approach (Figure C1 shows these counties). For about half of these storms, there was evidence of decreased risk of cardiovascular hospitalizations on the day of storm's closest approach. Across the entire storm period, while little evidence of increased risk was observed for cardiovascular hospitalizations, the risk for respiratory disease was consistently elevated across these storms (Table 4.2). For example, a cumulative RR of 1.66 (95% CI, 1.36–2.04) was estimated for respiratory disease hospitalizations among the elderly people in Broward County, FL from exposure to Hurricane Wilma (2005), resulting in an excess of 35 (95% CI, 23–45) hospital admissions for the entire storm period. While the estimated RRs of tropical cyclones on emergency hospital admission were often higher for respiratory disease than cardiovascular disease, the quantitative health impacts on respiratory disease admissions were a little lower for respiratory than cardiovascular disease, as shown by the attributable numbers: Hurricane Katrina in Broward County, FL, was associated with a cumulative RR of 1.15 (95% CI, 1.09–1.21) for cardiovascular disease, causing an estimated 39 excess hospitalizations (95% CI, 26–51), while this exposure was associated with a RR for respiratory hospitalizations of 1.36 (95% CI, 1.19–1.57), which translates to an estimated 20 excess respiratory hospitalizations (95% CI, 12–27). This results mainly from the observed number of respiratory disease hospitalizations in some counties being smaller than the observed number of hospitalizations from cardiovascular disease.

To investigate whether the estimated overall RRs for all tropical cyclone exposures identified were driven by these ten most severe tropical cyclone wind exposures, we compared the estimated RRs of cardiovascular and respiratory hospitalizations when calculated both with and without these ten exposures included in the analysis. While the risks for cardiovascular disease hospitalizations were very similar regardless of whether the ten severe storms were included in analysis (cumulative RRs: 1.14, [95% CI, 0.95–1.37] for all the storm exposures *vs.* 1.12, [95% CI, 0.91–1.38] for less severe storm exposures), the observed tropical cyclone-related risks for respiratory disease hospitalizations may partly be driven by those tropical cyclones exposures characterized by the most severe winds (cumulative RRs: 3.24, [95% CI, 2.34–4.50] for all storm exposures *vs.* 2.22, [95% CI, 1.53–3.21] for less severe storm exposures), as these associations were somewhat dampened when excluding these exposures from analysis (Figure 4.4). Also, given that the majority of the ten most severe wind-based storms were identified in the counties of Florida, which is the most storm-prone state, we also conducted additional sensitivity analyses investigating the most severe wind-based storms in counties out of Florida (Table C1).

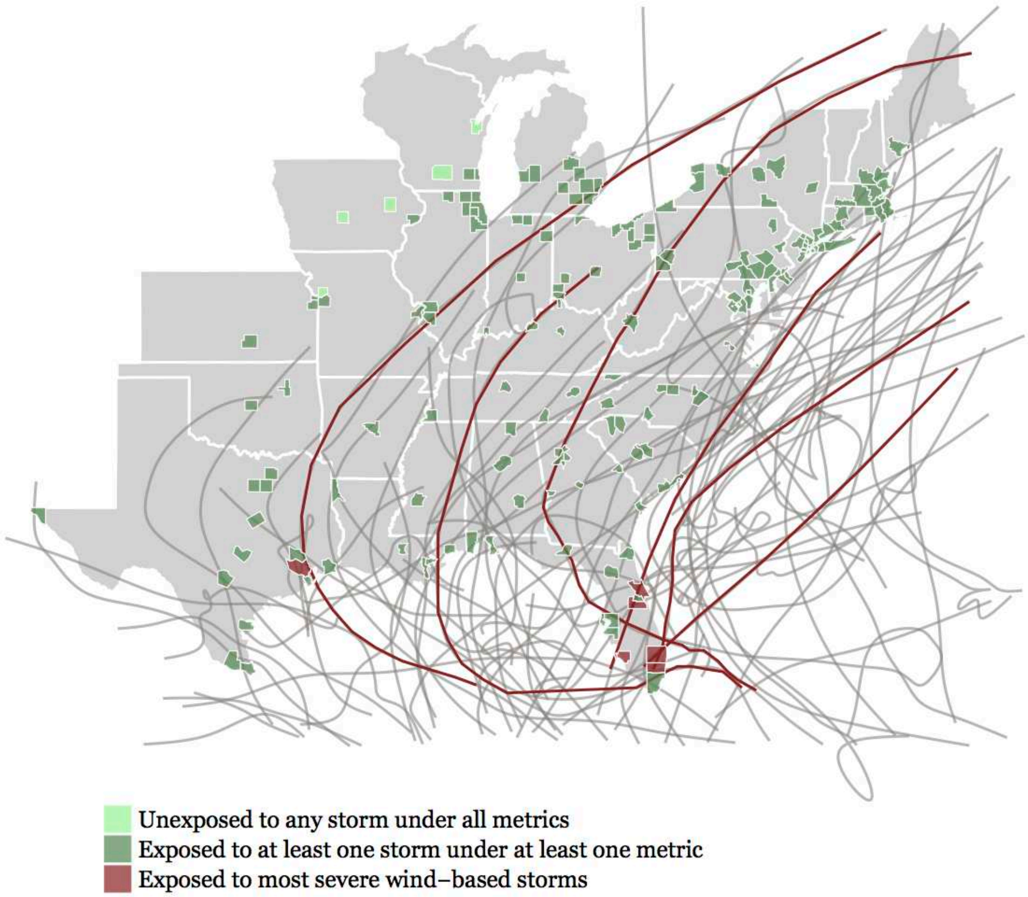

Figure 4.1 Map of study counties (180 total) and tracks of all Atlantic-basin tropical cyclones considered in this study. Storm tracks are shown in grey for all tropical cyclone (74 total) that came within 250 km of at least one county in the eastern U.S. between 1999 and 2010. Tracks in brown show the ten most severe wind-based storms.

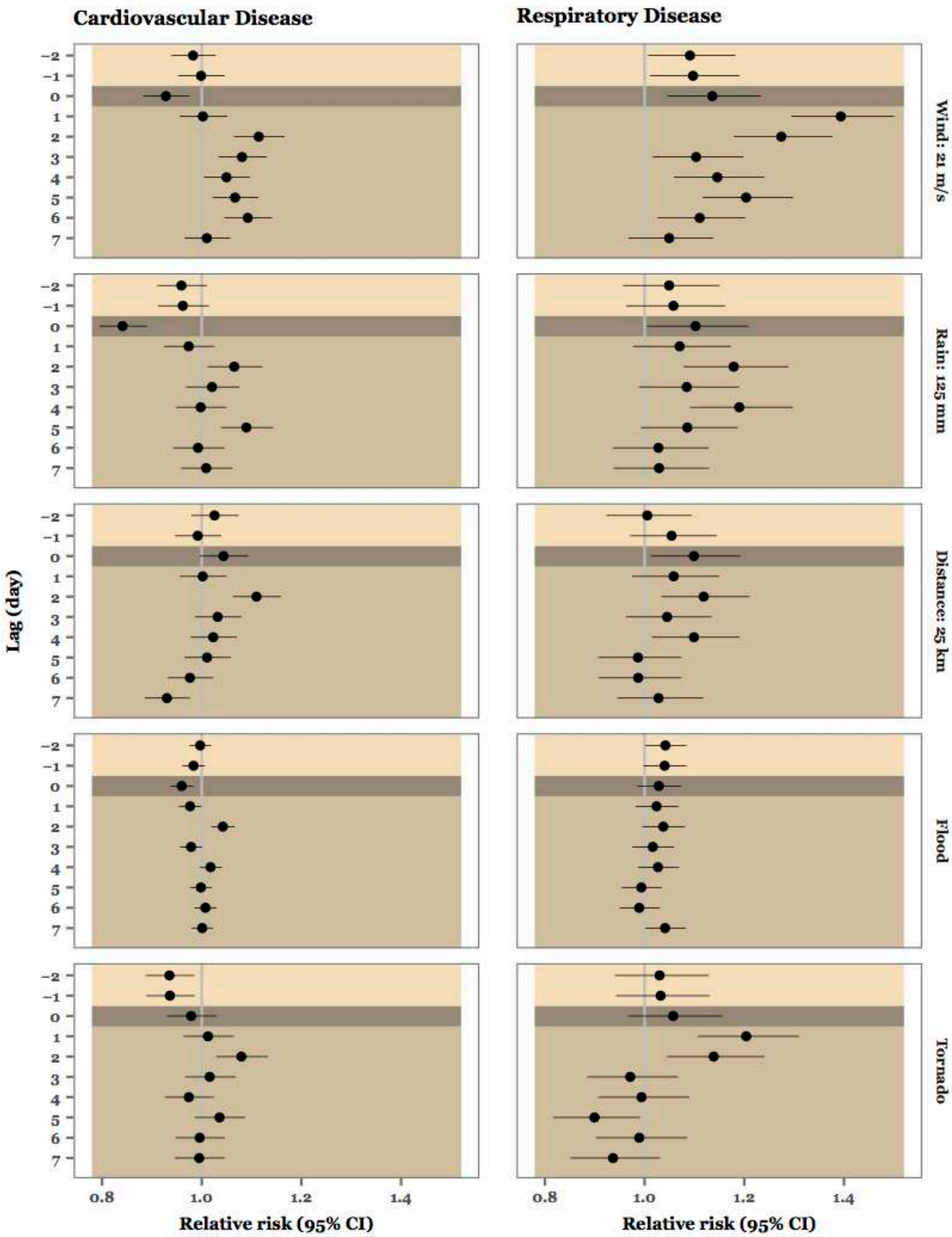

Figure 4.2 Estimates of lag-specific relative risks of hospitalizations on days during storm periods compared to matched days, for all storms and across all exposed counties, based on selected exposure metrics. Dots show point estimates and horizontal lines show 95% confidence intervals. The gray vertical line shows as a reference a relative risk of 1.

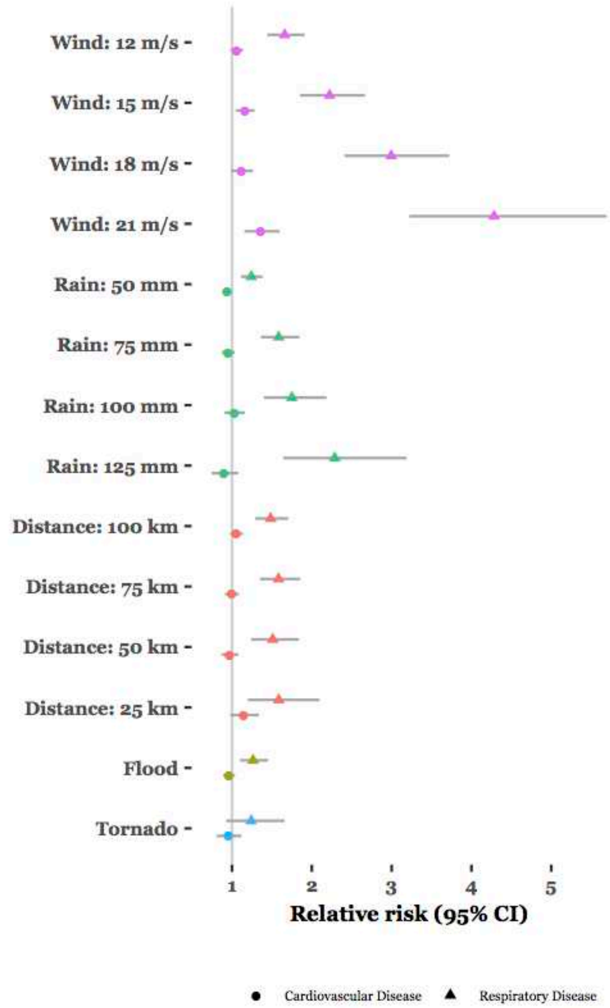

Figure 4.3 Estimates of cumulative relative risks of hospitalizations across the storm period considered (two days before to seven days after the date of storm's closest approach to the county) compared with matched non-storm periods, for all the storms and across all the exposed counties. Color is used to represent different exposure metrics. Dots show point estimates (with circle for cardiovascular disease and triangle for respiratory disease) and horizontal lines show 95% confidence intervals. The gray vertical line shows as a reference a relative risk of 1.

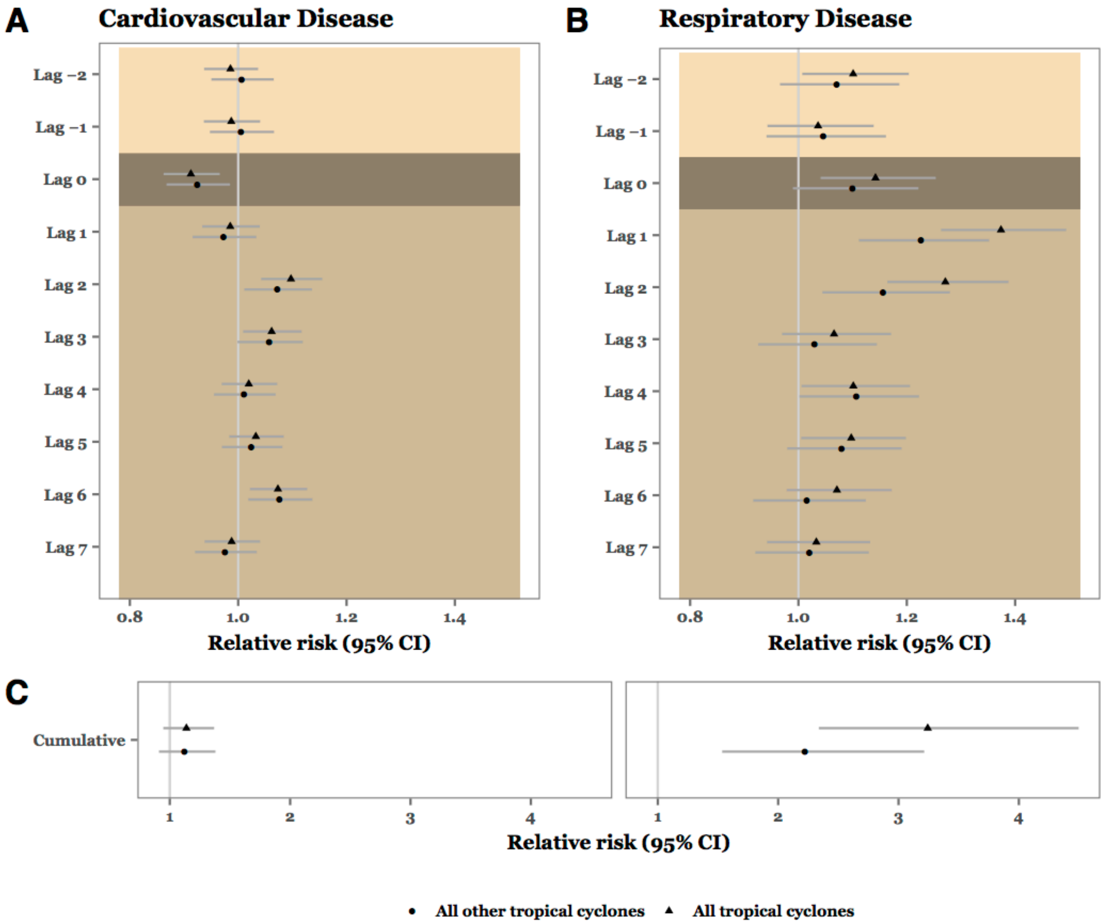

Figure 4.4 Estimates of relative risks (RR) of hospitalizations for all tropical cyclones (shown with triangle) and for tropical cyclones excluding the ten most severe wind-based ones (shown with circle). Dots show point estimates and horizontal lines show 95% confidence intervals. The gray vertical line shows as a reference a relative risk of 1. Estimates are shown for lag-specific RR for cardiovascular disease hospitalizations (A) and respiratory disease hospitalizations (B), as well as cumulative RR for cardiovascular and respiratory hospitalizations (C).

Table 4.1 Number of storm exposure and emergency hospital admissions under each of the exposure metrics investigated. For continuous exposure measurements (maximum sustained winds, cumulative rainfall, and distance to the storm track), the numbers of exposures are given for each of the thresholds of exposure considered in the study, from least to most constrictive.

Exposure	No. of counties	No. of storm exposures*	Cardiovascular disease		Respiratory disease	
			Storm-exposed days#	Matched unexposed days$	Storm-exposed days#	Matched unexposed days$
Wind						
12 m/s	145	558	63,125	62,982	19,739	19,070
14 m/s	116	338	41,917	41,758	13,305	12,632
18 m/s	86	217	30,167	29,976	9,830	9,085
21 m/s	54	123	17,964	17,383	5,965	5,277
Rain						
50 mm	169	919	106,046	103,194	32,907	32,026
75 mm	155	505	58,502	57,250	18,484	15,578
100 mm	123	267	30,155	29,450	9,434	8,924
125 mm	88	133	14,637	14,109	4,708	4,223
Distance						
100 km	159	590	66,879	65,391	20,886	20,087
75 km	150	452	52,099	51,373	16,363	15,673
50 km	136	309	35,324	35,126	11,300	10,829
25 km	95	149	17,991	17,831	5,640	5,434
Flood	151	570	69,594	67,778	21,225	20,556
Tornado	55	111	14,381	14,213	4,401	4,295

*Number of storms is the total number of storms under a given exposure metric (e.g., there were two storm exposures for county A, and three for county B, and those were the only two counties under a specific exposure metric, then the Number of storms was 5 (2+3).
Total hospital admissions for the entire storm period for all exposed counties under a certain exposure metric.
$ Total hospital admissions (averaged by ten as the number of matched days) for the entire storm period for all exposed counties under a certain exposure metric.

Table 4.2 Estimates of relative risk of hospitalizations for cardiovascular and respiratory diseases, as well as associated excess admission estimates, of ten most severe tropical cyclone wind exposures across the study storms, among counties with total number of Medicare beneficiaries greater than 50,000 on the day of storm's closest approach. Estimates are included for both the day of the storm's closest approach to the community ('Same-day estimates') and across the period from two days before to seven days after the storm's closest approach.

			Cardiovascular disease		Respiratory disease	
Storm	County	Wind (m/s)	Relative risk	Attributable number	Relative risk	Attributable number
Same-day estimates						
Wilma (2005)	Palm Beach County, FL	51.5	0.44 (0.36, 0.53)	-26 (-35, -18)	0.57 (0.18, 1.81)	-3 (-18, 2)
Charley (2004)	Lee County, FL	45.3	0.90 (0.48, 1.66)	-1 (-13, 5)	0.35 (0.03, 3.93)	-15 (-250, 6)
Charley (2004)	Orange County, FL	41.2	1.16 (0.76, 1.78)	3 (-7, 10)	1.52 (0.18, 12.87)	3 (-41, 8)
Ike (2008)	Harris County, TX	38.7	0.47 (0.18, 1.26)	-36 (-150, 7)	1.25 (0.58, 2.69)	3 (-10, 8)
Charley (2004)	Volusia County, FL	37.0	0.66 (0.22, 1.94)	-7 (-46, 6)	1.13 (0.39, 3.28)	0 (-5, 2)
Wilma (2005)	Broward County, FL	36.7	0.59 (0.42, 0.82)	-15 (-30, -5)	2.85 (1.56, 5.20)	8 (4, 10)
Katrina (2005)	Broward County, FL	33.5	1.18 (0.55, 2.53)	2 (-12, 9)	1.32 (0.31, 5.55)	2 (-15, 6)
Frances (2004)	Palm Beach County, FL	33.3	1.11 (0.75, 1.65)	4 (-12, 15)	0.83 (0.41, 1.70)	-1 (-10, 3)
Irene (1999)	Broward County, FL	33.3	0.66 (0.33, 1.34)	-15 (-62, 8)	0.70 (0.36, 1.36)	-6 (-25, 4)
Irene (1999)	Palm Beach County, FL	33.2	1.21 (0.54, 2.68)	4 (-18, 13)	2.88 (0.60, 13.75)	3 (-3, 5)
Cumulative estimates						
Wilma (2005)	Palm Beach County, FL	51.5	0.99 (0.84, 1.17)	-4 (-68, 51)	1.38 (0.97, 1.95)	32 (-3, 56)
Charley (2004)	Lee County, FL	45.3	1.07 (0.94, 1.21)	10 (-9, 27)	1.25 (0.90, 1.73)	10 (-6, 22)
Charley (2004)	Orange County, FL	41.2	1.20 (1.02, 1.41)	28 (3, 49)	1.44 (1.04, 1.99)	15 (2, 24)
Ike (2008)	Harris County, TX	38.7	0.93 (0.78, 1.10)	-33 (-117, 38)	1.44 (1.25, 1.65)	34 (22, 43)
Charley (2004)	Volusia County, FL	37.0	1.23 (0.95, 1.60)	18 (-5, 35)	1.08 (0.85, 1.38)	2 (-6, 9)
Wilma (2005)	Broward County, FL	36.7	1.00 (0.85, 1.18)	0 (-59, 51)	1.66 (1.36, 2.04)	35 (23, 45)
Katrina (2005)	Broward County, FL	33.5	1.15 (1.09, 1.21)	39 (26, 51)	1.36 (1.19, 1.57)	20 (12, 27)
Frances (2004)	Palm Beach County, FL	33.3	1.08 (0.92, 1.26)	24 (-27, 67)	1.35 (1.15, 1.59)	20 (10, 28)
Irene (1999)	Broward County, FL	33.3	0.89 (0.73, 1.09)	-38 (-117, 26)	1.10 (0.86, 1.41)	9 (-15, 27)
Irene (1999)	Palm Beach County, FL	33.2	0.86 (0.70, 1.07)	-59 (-163, 24)	1.40 (0.97, 2.00)	26 (-3, 45)

5. Discussion

We analyzed county-wide associations between tropical cyclones and emergency hospital admissions due to cardiovascular and respiratory disease in the Medicare populations in 175 exposed eastern U.S. counties between 1999 and 2010. For all the tropical cyclones considered in the study period and across all the exposed counties, the risks of storms on cardiovascular hospitalizations generally decreased on the day of the storm's closest approach, followed by a significant increase on the following days, with the largest increase often two days after the storm's closest approach. Risks for respiratory disease hospitalizations, in most cases, increased on the day of storm's closest approach, and remained elevated on a few days after. Given strong links between the severity of maximum sustained winds in a location and infrastructure damage form storms (21), tropical cyclone wind exposures may be particularly important in identifying storms associated with heightened risks of respiratory hospitalizations among Medicare beneficiaries. These findings add two important results to the paucity of research on the health impacts related to exposure to tropical cyclones among the elderly: first, the impact on emergency hospital admissions due to non-injury morbidity (investigated for cardiovascular and respiratory diseases) from exposure to tropical cyclones can increase substantially during storm exposure periods; and second, tropical cyclones with intense wind exposures may be particularly important in identifying high-risk storms associated with respiratory disease hospitalization among the elderly.

We observed an increase in risks of emergency Medicare hospitalizations for both cardiovascular and respiratory diseases in the period immediately following tropical cyclones' closest approaches to study counties during our study period, a finding that is largely in line with previous research conducted at a smaller scale (22). For example, in the two weeks following Hurricane Sandy's landfall, one study of highly impacted areas found a RR of 1.22 (95% CI, 1.16–1.28) for myocardial infarctions incidence and a RR of 1.07 (95% CI, 1.03–1.11) for stroke as compared to risks in the same weeks in the five previous years, using the data of all inpatient hospital discharges with cardiovascular diagnoses in New Jersey (22). Similarly, in the week following Hurricane Sandy's landfall, the total emergency hospitalization visits in a medical center of lower Manhattan, New York increased by 20% compared with the week before the storm and the proportion of hospitalizations due to chronic obstructive pulmonary disease (COPD) / asthma out of total hospital admissions increased approximately 3% compared with the previous week (18).

An increasing number of case studies have investigated the risk of individual storms on chronic disease (e.g., cardiovascular disease and hypertension) (12,22,26,33). However, there have been few studies examining associations between tropical cyclone exposure and respiratory disease risks beyond those associated with infectious disease outbreaks, which are often investigated in surveillance activities in the aftermath of storms (10). There are, however, plausible pathways through which tropical cyclone exposures could increase the risks of respiratory outcomes, especially in terms of increasing risks of acute outcomes in patients with preexisting respiratory disease (34). For example, tropical cyclones can cause power outages (35), which would increase exposure to outdoor conditions, including extreme heat and air pollution following the storm. Similarly, post-storm clean-up could increase exposures to these outdoor conditions (36). In a survey in the New Orleans area of workers engaged in post-Katrina clean-up, the prevalence rate ratio (PRR) for new-onset asthma was found to be elevated (PRR = 2.2, 95% CI, 0.8–6.2) during the period of clean-up (37). In our study, we indeed found substantially increased risk on emergency hospitalizations for respiratory disease among the elderly during tropical cyclone exposure periods up to a week following the storm compared with matched unexposed periods. This finding provides new insight into existing evidence on potential health outcomes associated with tropical cyclones.

The biological mechanisms by which tropical cyclones could increase the risk of cardiovascular and respiratory disease outcomes are unknown, but some hypotheses have been raised. Psychosocial stress may play an important role in the etiology of both cardiovascular disease (38,39) and respiratory disease (40–42). Furthermore, infrastructure damage caused by tropical cyclones can disrupt medical treatment or reduce medication adherence (35), which could lead to the onset of a new illness or the exacerbation of an existing illness. In fact, in a rapid assessment of the health status among older adults after Hurricane Charley in Florida, 28% of households reported that at least one older adult was impeded from receiving routine or follow-up care for a pre-existing condition (43). Finally, tropical cyclones could increase exposure to environmental hazards, such as mold and air pollution (44,45), both by increasing ambient concentrations of these exposures (e.g., flooding triggering mold growth, increased air pollution from burning debris or use of generators) or through making residents more exposed to ambient outdoor exposures than had the storm not occurred (e.g., because of power outages or an increase in time spent outdoors for post-storm clean-up). These secondary environmental exposures have been documented to be associated with increased risk in cardiovascular and respiratory disease (46).

When we investigated the timing of changes in hospitalization risks during the period from a few days before to a week after the storm's closest approach to a county, we observed a lagging pattern in risks of emergency hospital admissions for both cardiovascular and respiratory diseases. There was a substantial increase in the RRs of Medicare cardiorespiratory hospitalizations 1–4 days after the day of storm's closest approach, with a gradual return toward the expected risk without exposure (i.e., RR = 1) afterward. On the day of the storm's closest approach, we found an appreciable decrease in the risk for Medicare cardiovascular disease hospital admissions, with these estimated protective relative risks in some cases statistically significant (e.g., RR = 0.84 at lag 0 [95% CI, 0.79–0.89] under the strictest threshold of rain-based exposure metric). These findings on the timing of changing health risks are consistent with patterns found in previous, smaller-scale observational studies on the association between tropical cyclone exposure and hospital utilization (19,20,25,47,48). For example, one study found a significant drop in the number of Long Island (NY) emergency department (ED) visits for physical health problems on the day when Hurricane Sandy made landfall in New York, with the number of visits then slightly increased for two days following the storm compared to baseline values (19). Another study analyzed the impacts of three 2004 hurricanes on total number of ED patients in two central Florida emergency departments (47). In this study, EDs dropped significantly on the day of landfall compared with previous year (47) and increased on the following three days. These findings suggest that some tropical cyclone related factors could have contributed to the observed delay in treatments for patients. Tropical cyclones could cause important delays in seeking medical treatment for cardiovascular and respiratory disease through a number of pathways, including that the storm causes infrastructure damages such as suspension of public transportation, road closures, electricity outages, and impaired telecommunications. Those infrastructure damages may prevent patients from getting to the hospitals or calling emergency services for help (49). Such delays in medical care can lead to further adverse health outcomes; in previous studies, such delays have been found to increase subsequent risk of mortality across various setting and conditions (50,51).

For respiratory hospitalizations, we also found some evidence suggesting that particularly intense wind exposure may characterize the tropical cyclones most associated with elevated risks among Medicare beneficiaries. When we removed the ten most severe tropical cyclone wind exposures from our analysis of associated respiratory hospitalization risks, estimated RRs for respiratory disease hospitalizations were much smaller compared with estimates when all tropical cyclone exposures were considered (cumulative RR: 2.22 [95% CI, 1.53–3.21] *vs.* 3.24 [95% CI, 2.34–4.50]). A heightened risk from the most intense tropical cyclone wind exposures on respiratory disease might be related to elevated levels of other environmental exposures generated by strong winds during tropical cyclones, such as air pressure (52,53), pollen (54), and mold (e.g., mold levels doubled the day after Hurricane Ike in Hamilton County, OH (55)).

Although there is a large and growing body of research on the associations between some climate-related exposures, especially heat, and the health of older adults (31,56,57), research gaps remain for other climate-related exposures, including climate-related disasters like tropical cyclones (58). With coming climate change, the average intensity of tropical cyclones in the Atlantic basin is expected to increase (1). These storms will affect areas with large elderly populations (2). These expected future trends make it very important to focus more effort on understanding the potential health impacts of tropical cyclone exposures, especially on older adults. Our findings that emergency hospital admissions tend to be elevated during tropical cyclone exposures in a large Medicare population in the U.S., together with other recent studies on health risks among the elderly population associated with tropical cyclone exposure (especially for Hurricane Sandy) (16,18), add significantly to the previous knowledge base on the health impacts of tropical cyclones.

References

1. Walsh J, Wuebbles D, Hayhoe K, et al. Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program; 2014.

2. Zimmerman R, Restrepo CE, Nagorsky B, et al. Vulnerability of the elderly during Natural Hazard Events. Boulder, Colorado July 11-12, 2007.

3. Colby SL, Ortman JM. Projections of the size and composition of the U.S. population: 2014 to 2060. 2015;(https://www.census.gov/content/dam/Census/library/publications/2015/demo/p25-1143.pdf)

4. Mayhorn CB. Cognitive aging and the processing of hazard information and disaster warnings. *Natural Hazards Review*. 2005;6(4):165–170.

5. Daniel M. Who died during Hurricane Sandy, and why? 2012;(http://earthsky.org/earth/who-died-during-hurricane-sandy-and-why). (Accessed August 10, 2018)

6. Lew EO, Wetli CV. Mortality from Hurricane Andrew. *Journal of Forensic Science*. 1996;41(3):449–452.

7. Dominici F, Levy JI, Louis TA. Methodological challenges and contributions in disaster epidemiology. *Epidemiologic Reviews*. 2005;27(1):9–12.

8. Benson WF, Aldrich N. CDC's disaster planning goal: Protect vulnerable older adults. *CDC Health Aging Program*. 2007;

9. Ngo EB. When disasters and age collide: Reviewing vulnerability of the elderly. *Natural Hazards Review*. 2001;2(2):80–89.

10. Shultz JM, Russell J, Espinel Z. Epidemiology of tropical cyclones: The dynamics of disaster, disease, and development. *Epidemiologic Reviews*. 2005;27(1):21–35.

11. Disease Control C for, Prevention. Surveillance for illness and injury after Hurricane Katrina–New Orleans, Louisiana, September 8–25, 2005. *MMWR: Morbidity and Mortality Weekly Report*. 2005;54(40):1018–1021.

12. Sharma AJ, Weiss EC, Young SL, et al. Chronic disease and related conditions at emergency treatment facilities in the New Orleans area after Hurricane Katrina. *Disaster Medicine and Public Health Preparedness*. 2008;2(1):27–32.

13. Edwards TD, Young RA, Lowe AF. Caring for a surge of Hurricane Katrina evacuees in primary care clinics. *The Annals of Family Medicine*. 2007;5(2):170–174.

14. Centers for Disease Control and Prevention. Morbidity surveillance after Hurricane Katrina–Arkansas, Louisiana, Mississippi, and Texas, September 2005. *MMWR: Morbidity and Mortality Weekly Report*. 2006;55(26):727–731.

15. Quinn B, Baker R, Pratt J. Hurricane Andrew and a pediatric emergency department. *Annals of Emergency Medicine*. 1994;23(4):737–741.

16. McQuade L, Merriman B, Lyford M, et al. Emergency department and inpatient health care services utilization by the elderly population: Hurricane Sandy in the state of New Jersey. *Disaster Medicine and Public Health Preparedness*. 2018;1–9.

17. Dosa D, Feng Z, Hyer K, et al. Effects of Hurricane Katrina on nursing facility resident mortality, hospitalization, and functional decline. *Disaster Medicine and Public Health Preparedness*. 2010;4(S1):S28–S32.

18. Gotanda H, Fogel J, Husk G, et al. Hurricane Sandy: Impact on emergency department and hospital utilization by older adults in Lower Manhattan, New York (USA). *Prehospital and Disaster Medicine*. 2015;30(5):496–502.

19. Kim H, Schwartz RM, Hirsch J, et al. Effect of Hurricane Sandy on Long Island emergency departments visits. *Disaster Medicine and Public Health Preparedness*. 2016;10(3):344–350.

20. Smith CM, Graffeo CS. Regional impact of Hurricane Isabel on emergency departments in coastal southeastern Virginia. *Academic Emergency Medicine*. 2005;12(12):1201–1205.
21. Powell MD, Houston SH, Ares I. Real-time damage assessment in hurricanes. In: *Preprints, 21st Conf. on Hurricanes and Tropical Meteorology, Miami, FL, Amer. Meteor. Soc.* 1995:500–502.
22. Swerdel JN, Janevic TM, Cosgrove NM, et al. The effect of Hurricane Sandy on cardiovascular events in New Jersey. *Journal of the American Heart Association*. 2014;3(6):e001354.
23. Rath B, Young EA, Harris A, et al. Adverse respiratory symptoms and environmental exposures among children and adolescents following Hurricane Katrina. *Public Health Reports*. 2011;126(6):853–860.
24. Bayleyegn T, Wolkin A, Oberst K, et al. Rapid assessment of the needs and health status in Santa Rosa and Escambia counties, Florida, after Hurricane Ivan, September 2004. *Disaster Management & Response*. 2006;4(1):12–18.
25. Mortensen K, Dreyfuss Z. How many walked through the door?: The effect of Hurricane Katrina evacuees on Houston emergency departments. *Medical Care*. 2008;46(9):998–1001.
26. Greenough PG, Lappi MD, Hsu EB, et al. Burden of disease and health status among Hurricane Katrina–displaced persons in shelters: A population-based cluster sample. *Annals of Emergency Medicine*. 2008;51(4):426–432.
27. Landsea CW, Franklin JL. Atlantic hurricane database uncertainty and presentation of a new database format. *Monthly Weather Review*. 2013;141:3576–3592.
28. Anderson B, Yan M, Ferreri J, et al. hurricaneexposure: Explore and map county-level hurricane exposure in the United States. 2017.(https://cran.r-project.org/package=hurricaneexposure)
29. Anderson B, Schumacher A, Crosson W, et al. hurricaneexposuredata: Data characterizing exposure to hurricanes in United States counties. 2017.(https://github.com/geanders/hurricaneexposuredata)
30. Peng RD, Chang HH, Bell ML, et al. Coarse particulate matter air pollution and hospital admissions for cardiovascular and respiratory diseases among Medicare patients. *Journal of the American Medical Association*. 2008;299(18):2172–2179.
31. Anderson GB, Dominici F, Wang Y, et al. Heat-related emergency hospitalizations for respiratory diseases in the Medicare population. *American journal of respiratory and critical care medicine*. 2013;187(10):1098–1103.
32. Gasparrini A. Modeling exposure-lag-response associations with distributed lag non-linear models. *Statistics in Medicine*. 2014;33(5):881–899.
33. Krousel-Wood MA, Islam T, Muntner P, et al. Medication adherence in older clinic patients with hypertension after Hurricane Katrina: Implications for clinical practice and disaster management. *The American Journal of the Medical Sciences*. 2008;336(2):99–104.
34. Bernstein AS, Rice MB. Lungs in a warming world: Climate change and respiratory health. *Chest*. 2013;143(5):1455–1459.
35. Klinger C, Owen Landeg VM. Power outages, extreme events and health: A systematic review of the literature from 2011–2012. *PLoS Currents*. 2014;6.
36. Caillouët KA, Michaels SR, Xiong X, et al. Increase in West Nile neuroinvasive disease after Hurricane Katrina. *Emerging Infectious Diseases*. 2008;14(5):804.
37. Rando RJ, Lefante JJ, Freyder LM, et al. Respiratory health effects associated with restoration work in post-Hurricane Katrina New Orleans. *Journal of Environmental and Public Health*. 2012;2012.
38. Bhattacharyya MR, Steptoe A. Emotional triggers of acute coronary syndromes: Strength of evidence, biological processes, and clinical i8mplications. *Progress in Cardiovascular Diseases*. 2007;49(5):353–365.
39. Steptoe A, Kivimäki M. Stress and cardiovascular disease. *Nature Reviews Cardiology*. 2012;9(6):360.

40. Cohen S. Psychological stress and susceptibility to upper respiratory infections. *American Journal of Respiratory and Critical Care Medicine*. 1995;152(4):S53.

41. Pedersen A, Zachariae R, Bovbjerg DH. Influence of psychological stress on upper respiratory infection—a meta-analysis of prospective studies. *Psychosomatic Medicine*. 2010;72(8):823–832.

42. Rietveld S, Everaerd W, Creer T. Stress-induced asthma: A review of research and potential mechanisms. *Clinical and Experimental Allergy*. 2000;30(8):1058.

43. Centers for Disease Control and Prevention. Rapid assessment of the needs and health status of older adults after Hurricane Charley–Charlotte, DeSoto, and Hardee Counties, Florida, August 27-31, 2004. *MMWR. Morbidity and Mortality Weekly Report*. 2004;53(36):837.

44. Barbeau DN, Grimsley LF, White LE, et al. Mold exposure and health effects following Hurricanes Katrina and Rita. *Annual Review of Public Health*. 2010;31:165–178.

45. Chen B, Shawn L, Connors N, et al. Carbon monoxide exposures in New York City following Hurricane Sandy in 2012. *Clinical Toxicology*. 2013;51(9):879–885.

46. Mendell MJ, Mirer AG, Cheung K, et al. Respiratory and allergic health effects of dampness, mold, and dampness-related agents: A review of the epidemiologic evidence. *Environmental Health Perspectives*. 2011;119(6):748.

47. Platz E, Cooper HP, Silvestri S, et al. The impact of a series of hurricanes on the visits to two central Florida emergency departments. *The Journal of Emergency Medicine*. 2007;33(1):39–46.

48. Greenstein J, Chacko J, Ardolic B, et al. Impact of Hurricane Sandy on the Staten Island University Hospital emergency department. *Prehospital and Disaster Medicine*. 2016;31(3):335–339.

49. Jangi S. Facing uncertainty—dispatch from Beth Israel Medical Center, Manhattan. *New England Journal of Medicine*. 2012;367(24):2267–2269.

50. Chalfin DB, Trzeciak S, Likourezos A, et al. Impact of delayed transfer of critically ill patients from the emergency department to the intensive care unit. *Critical Care Medicine*. 2007;35(6):1477–1483.

51. Chan PS, Krumholz HM, Nichol G, et al. Delayed time to defibrillation after in-hospital cardiac arrest. *New England Journal of Medicine*. 2008;358(1):9–17.

52. Boycott A, Haldane J. The effects of low atmospheric pressures on respiration. *The Journal of physiology*. 1908;37(5-6):355–377.

53. Cogo A. The lung at high altitude. *Multidisciplinary Respiratory Medicine*. 2011;6(1):14.

54. D'Amato G, Liccardi G, Frenguelli G. Thunderstorm-asthma and pollen allergy. *Allergy*. 2007;62(1):11–16.

55. Schmidlin TW. Public health consequences of the 2008 Hurricane Ike windstorm in Ohio, USA. *Natural Hazards*. 2011;58(1):235–249.

56. Bobb JF, Obermeyer Z, Wang Y, et al. Cause-specific risk of hospital admission related to extreme heat in older adults. *Journal of the American Medical Association*. 2014;312(24):2659–2667.

57. Gronlund CJ, Zanobetti A, Schwartz JD, et al. Heat, heat waves, and hospital admissions among the elderly in the United States, 1992–2006. *Environmental Health Perspectives*. 2014;122(11):1187.

58. Gamble JL, Hurley BJ, Schultz PA, et al. Climate change and older Americans: State of the science. *Environmental Health Perspectives*. 2013;121(1):15.

Chapter 5: Main findings, limitations, and future work

1. Main findings

In this dissertation, we aimed to examine the community-wide change in health outcome rates during natural disasters relative to the expected rates in the absence of disasters. To do this, we compared community-wide rates of health outcomes observed during natural disasters to the health outcome rates on matched unexposed days in the same community. Our results can provide new evidence on how natural disasters affect human health, contributing to and complementing the large base of existing literature generated using a traditional surveillance approach to identify health outcomes attributable to a disaster on a case-by-case basis.

Chapter 2: Changes in the community-wide rates of all-cause, circulatory, respiratory, and accidental mortality in Beijing, China during the July 2012 flood. In this study, we examined the community-wide mortality risks among Beijing residents from exposure to a severe flood. Compared with the matched non-flood days, mortality rates were substantially higher during the flood period for all-cause, circulatory, and accidental mortality, with the highest risks observed on the peak flood day. On the peak flood day, the flood-associated relative risks (RRs) of mortality were 1.34 (95% confidence interval: 1.11–1.61), 1.37 (1.01–1.85), and 4.40 (2.98–6.51) for all-cause, circulatory, and accidental mortality, respectively. No evidence of increased risk of respiratory mortality was found in this study. We estimated a total of 79 excess deaths among Beijing residents on July 21–22, 2012, as compared with expected mortality rates had the flood not occurred; by contrast, only 34 deaths were reported among Beijing residents in a study estimating the fatality toll of this flood using a traditional surveillance approach. Our results indicate considerable impacts of this flood on public health, and that much of this impact may come from increased risk of non-accidental deaths. To our knowledge, this is the first study analyzing the community-wide changes in mortality rates during the 2012 flood in Beijing, and one of the first to do so for any major flood worldwide. This study offers critical evidence in assessing flood-related health impacts, as urban flooding is expected to become more frequent and severe in China.

Chapter 3: Tropical cyclones and associated risks to all-cause, accidental, cardiovascular, and respiratory mortality in 70 United States communities, 1988–2005. We analyzed the community-wide change in mortality rates during storm-exposed days compared to similar unexposed days using multi-community, multi-year data in eastern half of U.S. We assessed tropical cyclone exposure using five metrics: distance to storm track; cumulative rainfall; maximum sustained wind speed; flooding; and tornadoes. From 1988 to 2005, 92 Atlantic Basin tropical cyclones made landfall or passed near the eastern half of U.S., and 70 of our study communities were exposed to at least one of these storms. During tropical cyclone wind exposures, community-wide mortality risks were generally elevated, with highest risks typically on the day of the storm's closest approach. For the strongest wind exposures, the RRs of mortality on the day of storm's closest approach were 1.42 (95% CI, 1.36–1.49), 12.03 (10.87–13.32), 1.15 (1.06–1.24), 1.12 (0.92–1.38) for all-cause, accidental, cardiovascular, and respiratory mortality, respectively, across all exposed communities. These observed associations may be dominated by extremely high risks during the few most severe tropical cyclone wind exposures; for example, a RR of 38.69 (7.37–203.21) was observed for cardiovascular mortality from Hurricane Katrina in New Orleans, the third most severe wind-based storm exposure observed in our study. Our findings on community-wide mortality risks from tropical cyclones add two important insights to results from traditional surveillance: first, the health impact of tropical cyclones on non-accidental mortality can, in some cases, be much greater than identified in case-by-case surveillance studies and, second, intense winds characterize many of the tropical cyclone exposures with particularly high associated risks of non-accidental mortality.

Chapter 4: Tropical cyclone-associated risks of emergency Medicare hospital admission for cardiorespiratory diseases in 175 United States counties, 1999–2010. We analyzed the county-wide associations between tropical cyclone exposures and emergency hospital admissions among Medicare beneficiaries in a large collection of eastern U.S. counties. Over our study period (1999–2010), 74 Atlantic Basin tropical cyclones were considered based on U.S. landfall or close approach, with 175 out of 180 study counties exposed to at least one storm based on at least one exposure metric. Among Medicare beneficiaries, tropical cyclone exposure was typically associated with a decreased risk in cardiovascular hospitalization on the day of storm's closest approach, followed by a significant increase in risk on days following the storm, with the largest increase often found two days after the storm's closest approach. Risks for respiratory disease hospitalizations, in most cases, increased on the day of the storm's closest approach, with the risk continuing to increase following the storm. Cumulative risks of respiratory hospitalizations across the period from two days before to seven days after the storm were increased under all storm exposure metrics considered, when considering all storm exposures observed in the study (i.e., for all storms and across all exposed study counties); these risks remained significantly elevated (RR = 2.22, 95% CI, 1.53–3.21) even when the ten most severe tropical cyclone wind exposures were excluded from analysis (i.e., analysis was restricted to tropical cyclone exposures with less severe winds). By conducting an examination of the county-wide risks associated with tropical cyclone exposures on emergency hospitalizations among a large study population of Americans aged 65 and older, our results add two important findings to the paucity of literature on health impacts among the elderly associated with exposure to tropical cyclones: first, there is strong evidence that risks of Medicare emergency hospital admissions due to non-injury morbidity (investigated here for cardiovascular and respiratory diseases) are elevated during the period surrounding tropical cyclone exposures; second, tropical cyclones with most intense wind exposures may be particularly important in identifying high-risk storms associated with respiratory disease hospitalization among the elderly population, although elevated risks are also observed during less severe tropical cyclone wind exposures.

Comparing results across the three projects. In Chapter 2, we found a substantially increased risk in circulatory mortality among Beijing residents during exposure to a severe flood event. In contrast, in Chapter 3, under the flood-based exposure metric, there was little evidence of increased risk in cardiovascular mortality associated with tropical cyclones across our study communities in the U.S. As discussed in the previous Chapters, natural disasters could increase the risk of non-accidental health outcomes through infrastructure damage, such as suspension of public transportation, road closures, electricity outages, and impaired telecommunications. The different findings on mortality risk in relation to flooding (in Chapter 2 and 3) could be in part attribute to the characteristics of flooding (including the severity of the flooding) and study communities, all factors that could help determine the amount of infrastructure damage caused by a flood event. First, the flood event investigated in Chapter 2 and those included in Chapter 3 may differ in characteristics such as the intensity of the event that caused the flooding and in the secondary hazards generated by the flooding. In Chapter 2, the flooding was triggered by extreme rainfall and exacerbated by Beijing's topography. The most heavily impacted regions were mountainous, rather than flat, regions of the city, where the flood also triggered landslides. Transportation and communication systems were seriously affected in these regions, making it hard for residents to access healthcare. In contrast, the tropical cyclone-associated flood events included in Chapter 3 may be less severe than the one in Beijing, or may have affected more sparsely populated regions in the affected communities. Second, community-level factors could also play a role in how flooding affects residents' health. Given the dense population and heavy reliance on public transportation in Beijing, Beijing may be particularly susceptible to infrastructure damage caused by flooding. In the context of tropical cyclones (Chapter 3), communities may have had more time, given tropical cyclone forecasts and warnings, to prepare for storms in advance and evacuate from areas prone to flooding, thus residents may be less affected by flooding during tropical cyclones in the communities represented in the Chapter 3 study.

In Chapter 3 and 4, we examined community-wide mortality and hospitalization risks associated with tropical cyclone exposure in the U.S., and in some cases the patterns in risks observed for hospitalizations for a certain cause varied from the patterns for mortality risks. While little evidence was observed for increased respiratory mortality risk among all the community residents from exposure to tropical cyclones (Chapter 3), we found a substantially elevated risk in emergency hospital admissions associated with tropical cyclones among Medicare beneficiaries (Chapter 4). Two factors may in part account for the inconsistency in observed patterns in risk for these two respiratory outcomes during tropical cyclone exposures. First, the study population (which is limited to those 65 years and older) in Chapter 4 could be more vulnerable to tropical cyclones compared with the study population in Chapter 3, which covers the all residents in each study community, as the study population in Chapter 4 may have higher underlying prevalence for a number of health conditions (i.e., vision/hearing impairments, chronic medical conditions) that could increase susceptibility to acute respiratory-related risks triggered by a disaster. Second, the potential pathway linking tropical cyclone exposures and non-accidental health outcomes could be another important source of the observed differences in risks of hospitalization outcomes versus mortality outcomes observed in this study. Infrastructure damage caused by tropical cyclones can disrupt medical treatment or reduce medication adherence, which could be sufficient to lead to hospitalizations, but not the more severe outcome of mortality for respiratory outcomes. In Chapter 4, the health outcome investigated was emergency hospital admission and the subsequent health outcomes among patients after hospitalized were not considered. Patients could survive if they received timely medical treatment or die if they were too sick to save in the hospitals. In Chapter 3, although elevated risks in respiratory mortality were not consistently observed across all the exposure metrics considered, we indeed observed evidence of appreciable increased risk in respiratory mortality in a few cases (e.g., when using the strictest threshold of wind-based exposure (Figure 3.3)). Also, the results from Chapter 3 and 4 both indicated that intense wind exposure can characterize many of the tropical cyclone exposures with particularly high associated risks for non-accidental health outcomes, as the physical damage caused by tropical cyclones is strongly associated with the speed of the winds from the storm at a location. Thus, while tropical cyclones, in most cases, may cause or exacerbate respiratory illness in the affected population, they may only result in respiratory mortality when the physical infrastructure has been extremely damaged (for example, increased risk in respiratory mortality was found in communities where the maximum sustained wind speed > 21 m/s, as shown in Figure 3.3).

2. Strengths and limitations

Strengths

In this dissertation, we assessed the community-wide health risks from exposure to two types of climate-related natural disasters, a severe flood and tropical cyclones. This dissertation can help deepen the current understanding of health effects from exposure to flooding and tropical cyclones through three important findings. First, flooding and tropical cyclones can be associated with substantial increases in the risks of non-accidental health outcomes at the community level, an association which has been largely missed or underestimated in the literature based on traditional surveillance following disasters, the method often used to generate official fatality tolls following a disaster. Second, Atlantic Basin tropical cyclones can substantially increase the risk of emergency hospital admissions due to cardiovascular and respiratory diseases in a diverse population aged 65 and older in U.S. communities. This finding contributes to the limited existing literature on storm-associated effects on non-injury health outcome. Third, severe winds may characterize the tropical cyclone exposures associated with particularly high elevated risks of non-accidental mortality and of Medicare respiratory hospitalizations. These findings highlight the range of health risks that may be caused by flood and tropical cyclone exposures and can help improve our understanding of the pathways and mechanisms of how these climate-related disaster exposures affect human health.

These key findings would not only add important insights to existing knowledge based on traditional surveillance studies of floods and tropical cyclones, but they also highlight a strength of our approach of using a community-wide assessment of mortality or hospitalization risks during disaster exposures compared to matched unexposed days. Although similar techniques have been extensively used to assess community-wide health effects from exposure to other climate-related disasters—including heatwaves (1), wildfires (2), droughts (3), and snowstorms (4)—research gaps remain for other climate-related disasters like floods and tropical cyclones. Moreover, this approach can be readily applied in examining community-wide health effects from exposure to other types of natural disasters, and by using matched unexposed days for comparison rather than days within the same year as the disaster, it may be possible to modify the method to explore the longer-term (i.e., over several months to a year) health effects associated with exposure to natural disasters.

Limitations

In these studies, our aim was to estimate the change in community-wide health outcome rates during a natural disaster as compared to the rate expected without the disaster. To try to estimate this value, we conducted an observational study using daily counts of the health outcome of interest, and compared the health outcome rates on the event-exposed days to those on the matched unexposed days, with additional model control for year and day of week. Many of the limitations of our study are linked to potential ways in which our method of estimating this disaster-associated risk (through a matched analysis) may struggle to estimate the effect we care about (how community-wide rates of a health outcome differed during the exposure compared to the counterfactual of no exposure on the same day).

First, there is likely **residual confounding** within our analysis, as is the case in almost all observational studies, as well as in many randomized experiments (5). For each study community, we used a population of the community on matched unexposed days as an approximation of the unobserved counterfactual (i.e., had the disaster not occurred on the days of the observed disaster). This approach could lead to confounding because the matched unexposed days were selected from different years, introducing non-exchangeability between the exposed and unexposed members of the study population (see more discussion in Chapter 1). Across different years, the population of a community may vary in many characteristics that are related to the distribution of health outcomes, such as age distribution, socioeconomic status, and chronic disease prevalence. To address this confounding, we adjusted for year in the regression model. However, residual confounding could remain if this is an inadequate adjustment of confounding from longer-term temporal trends that affect health outcome distributions in the community.

Residual confounding from incomplete control for long-term changes in the study population can have a different level of importance for a single-event, single-community analysis (Chapter 2) as compared to a multi-event, multi-community analysis (Chapters 3 and 4). In Chapter 2, we investigated community-wide mortality risks of a severe flooding event in 2012 in Beijing, China, using five years of data of daily death counts (2008–2012) to compare mortality rates on the flood-exposed day (2012) to rates on matched similar (same month of year, and same day of week as the flood-exposed day) unexposed days in previous years (2008–2011). We adjusted for a linear trend of year in the regression model, which helps to adjust for some of the potential confounding by year, but may not completely prevent residual confounding associated with year-to-year changes in the study population. In Chapter 3 and 4, we explored the mortality and morbidity risk of all the Atlantic Basin tropical cyclone exposures and across all the exposed communities over multi-year study period (1988–2005, and 1999–2010). Given that tropical cyclones in the Atlantic Basin generally run from June to November, with a peak in frequency around September, we matched storm-exposed day to similar unexposed days by day of year, to adjust for potential confounding by season. We applied regression model to the matched multi-year data, with year included as an indicator variable to adjust for potential confounding related to long-term trends. With a long study period, covering multiple storms in many different study years, exposed and unexposed members of the study population should have a more even distribution over study years, and the strict matching based on seasonality should ensure an equal distribution of seasonal factors related to health outcomes between the exposed and unexposed populations. Thus, the magnitude of residual confounding is likely less of a concern than that in the Chapter 1 (a single-event, single-community study), although some potential for residual confounding remains even in these larger-scale studies.

Second, **exposure misclassification** could occur in all three studies. In Chapter 2, given that the intensity of rainfall was heterogeneous across Beijing (6,7), it is likely that some areas of Beijing were heavily impacted by this flood, while other areas were mildly or even not impacted by the flood. In our analysis, we were not able to measure flood exposure at a fine geographic scale, but rather assigned residents throughout Beijing residents as exposed to flood on the exposed day. Therefore, residents in some areas of Beijing might have been misclassified as exposed to flood on the flood day. In contrast, on the matched unexposed days (same time period in previous years), exposure misclassification is much less likely, because there were no other major flood in these years in Beijing. Thus, flood exposure misclassification was likely differential in the compared groups, with some of the study population assessed as exposed to the flood actually unexposed and so expected to have a similar risk of mortality as the population assessed as unexposed, rather than a flood-elevated risk. Under this circumstance, our estimated RR would likely be biased toward the null.

In Chapter 3 and 4, exposure misclassification may occur when using flood- and tornado-based exposure metrics, both of which we obtained data from the NOAA Storm Events database. Given that existing evidence demonstrated the likelihood of underreporting tornado occurrence in the Storm Events database (8), missingness in the reporting of events in this database could result in misclassification of storm exposure in our study. Specifically, individuals residing in certain areas where an unrecorded tornado occurred during our study period would be misclassified as unexposed to storm. We believe this effect, however, would have negligible influence on our study estimates, since tornadoes are such rare events, and so it is unlikely that many, if any, of the matched unexposed days selected within our study had unreported tornadoes.

Another limitation stems from using **outcome misclassification** in Chapters 2 and 3. Although the vast majority of the deaths should have been correctly classified according to the primary cause of death listed, there might be a chance of outcome misclassification (in this context, not counting a death that occurred), in particular in a extremely devastating disaster. For example, during a really bad disaster (e.g., Hurricane Katrina, Hurricane Maria, a very severe earthquake), some people might be killed but their bodies not found or, if they are found, not identifiable. Such deaths would lack a death certificate or would have a death certificate that cannot be linked to the decadent's county of residence, so these deaths would not be included in daily counts of deaths among county residents. Also, a lot of people might evacuate before or after some disasters. While the mortality counts used in our analysis are for residents of a community, regardless of the location of the death, in the case of massive evacuations, there could be failures in collecting and processing administrative data and so linking these some of these deaths to the correct residential location. One study examined Hurricane Katrina deaths using both Louisiana and out-of-state death certificates, as well as a database of victims, as confirmed by the Disaster Mortuary Operational Response Team (DMORT) (9). The DMORT database listed 171 storm victims who were not identified as Hurricane Katrina-related in the death certificates/vital records. Also, over 40 of these deaths lacked specific dates of death or the date when the body was found. In this scenario—some deaths are unreported in administrative daily death count data from vital statistics—our estimates of the association between disaster exposure and mortality rates would likely be biased towards the null.

Fourth, potential **effect modification** on the associations between tropical cyclone exposures and mortality and morbidity were not evaluated in this dissertation. In Chapters 3 and 4, we found some evidence that the risks associated with tropical cyclone exposures vary across storms, and that in particular severe wind exposures might play a role in this variation. Other characteristics of the storm (e.g., cumulative rainfall, storm surge), as well as characteristics of the community in which the exposure happens (e.g., demographics, percent of roads or homes in flood plains, vulnerability of the power system to tropical cyclone hazards, preparedness and resiliency of the emergency health system) could modify the estimated associations. This is an area that could be explored in future research.

3. Implications

Implications for further research

Explore the mechanisms linking natural disasters and non-accidental health consequences. In this dissertation, we observed evidence that a severe flood event and tropical cyclone exposures were associated with increased risks on mortality, including cardiovascular mortality, and non-accidental emergency hospital admissions in the Medicare population. Since the biological mechanisms through which flood and storm exposures increase risk of mortality and morbidity from non-accidental causes are not well understood, a key next step in research is to clarify the pathways and mechanisms. As we discussed in previous chapters, flooding and tropical cyclones may affect non-accidental health outcomes by changing a variety of mediator factors on the pathway between tropical cyclone hazards (e.g., wind, rain, flooding, tornadoes) and fatal and non-fatal health outcomes, as evidenced by previous reports and investigations. For example, strong winds and flooding from a tropical cyclone can cause power outages (10), which increases residents' exposure to outdoor conditions, including extreme heat (11). Post-storm clean-up can also increase average exposure within a community to outdoor conditions (12). Exposure to extreme heat is a direct risk factor for both accidental (e.g., heat stroke) and non-accidental deaths (11,13,14). Disruption in health care during natural disaster can be one of the primary causes of the substantial public health impacts, as shown in studies of some recent hurricanes in the U.S. (15–17), and patients with chronic diseases are likely particularly vulnerable to the interruption in medical care. To mitigate and prevent individuals from morbidity and mortality during natural disasters, future studies are needed to figure out the pathways through which natural disaster exposures might cause increased risks for adverse health outcomes.

Examine other possible health outcomes with associations of natural disasters. Given these suggestive pathways linking natural disasters and adverse health outcomes, especially the potential pathway through disruption in health care during disasters, some other health outcomes may also be associated with natural disaster exposures. A number of studies have identified that, due to medical infrastructure damage from tropical cyclones (16,18) and earthquakes (19,20), health outcomes related to kidney disease increased in the aftermath of these disasters. Anecdotal records and surveys have also shown that many patients reported loss of health care treatment during a severe hurricane, which could increase the burden of several chronic disease, including hypertension, diabetes, and cancer (21–25). Hence, more research is needed to explore a spectrum of possible health outcomes which may be threatened by natural disasters.

Project potential future health burdens of tropical cyclone exposures under climate change scenarios. We observed evidence that intense wind exposures generated by tropical cyclones could be particularly important in identifying storms with high-risk on non-accidental health outcomes. By the late 21th century, the frequency of the strongest storms (maximum sustained wind > 58 m/s) is projected to increase about 30% (26–28) [is this worldwide or in the Atlantic basin? clarify your wording here]. Combining these projections with our findings, there is the potential for tropical cyclones to have an increasing health impact in the future.

Implications for practice

Our findings based on community-wide assessment could help raise awareness of the potential risks on non-accidental health outcomes associated with flooding and tropical cyclones among public health officials, including among physician certifying death certificates in a disaster. As evidenced in some studies (29–31), disaster surveillance, given its inherent approach based on case-by-case attribution, could potentially undercount the number of death related to a disaster, especially those indirectly related to disaster. After Hurricane Maria (2017) made landfall in Puerto Rico, several independent investigations and press reports demonstrated that the official reported count of deaths caused by the hurricane was substantially underestimated (15,32–35). One (32) also evaluated how Puerto Rico reported deaths in disasters and how they implement the CDC guidelines (36). In that report, the authors pointed out that one primary cause for undercounting death caused by Hurricane Maria was inadequate personnel training in death certificate completion, especially during a disaster. When the authors interviewed these physicians, some "expressed reluctance to relate deaths to hurricanes due to concern about the subjectivity of this determination and about liability" (page iii, (32)). Further, according to an assessment conducted by the Disaster Epidemiology Subcommittee of the Council of State and Territorial Epidemiologists (CSTE) in the U.S., the 53 responding jurisdictions differed widely in how they conducted disaster surveillance, and only about half had specific group of public health officials responsible for disaster surveillance (37). Thus, our findings of considerable risks on non-accidental health outcomes associated with flood and tropical cyclones, based on a large-scale study of many communities and events in the case of tropical cyclones, help highlight the role these disasters can play in increasing risks of both accidental and non-accidental deaths in exposed communities.

Our findings, based on community-wide assessment of changes in health outcomes rates during disasters, could help raise awareness of the potential risks disaster exposures may cause from some non-accidental health outcomes among the public, especially among people who are at high risks of these non-accidental causes of outcomes. Due to in part to interruptions in medical treatment that can result from natural disasters, patients with pre-existing medical conditions can struggle during disasters to maintain compliance with their treatment and medications. The vulnerability for dialysis patients in natural disasters have gotten particular attention in past few decades, especially after the 2005 Atlantic hurricane season (16,38,39), resulting in study findings that helped both dialysis patients and dialysis providers become better prepared to face natural disasters: dialysis providers have implemented extensive disaster plans (38,39), and many dialysis patients can now evacuate without the concern that they would not be able to receive treatment in the evacuation areas (40). However, disaster preparedness and planning for many other vulnerable individuals and chronic disease patients have not been as systemically and widely discussed. In this dissertation, we observed evidence of substantial risks for some broad non-accidental health outcomes (i.e., cardiovascular and respiratory morbidity and mortality) from exposure to flooding and tropical cyclones. This finding underscores the significance of mitigating the effects of natural disasters on vulnerable individuals and chronic disease patients, through appropriate and specific disaster preparedness, planning, and education.

Our findings of substantial effect of storm exposures on emergency hospital admissions due to non-injury medical conditions in the elderly population, together with several single-storm reports on large proportion of non-injury emergency department visits after tropical cyclones (41,42), would be useful for further disaster medical planning. In this dissertation, we found noticeable delayed risks (with the largest increase often on the one or two days after the storm-exposed day) for cardiovascular and respiratory hospitalizations in a large elderly population, suggesting patients might have difficulty in accessing hospitals on the day of storm's approaching. This finding creates a hypothesis for one pathway of tropical cyclone health impacts among the elderly, and future research in this direction would be extremely useful for further disaster medical planning. For example, if road closures are a key step in the causal pathway, by making it harder to access medical care during and following a disaster, then knowing that could help inform longer-term community disaster planning and management, including steps like restricting the building of new roads in flood-prone areas and improving tree-trimming and other tree management near roadways, especially before each year's hurricane season, to limit road closures from fallen trees.

References

1. Bobb JF, Obermeyer Z, Wang Y, et al. Cause-specific risk of hospital admission related to extreme heat in older adults. *Journal of the American Medical Association*. 2014;312(24):2659–2667.
2. Liu JC, Wilson A, Mickley LJ, et al. Wildfire-specific fine particulate matter and risk of hospital admissions in urban and rural counties. *Epidemiology (Cambridge, Mass.)*. 2017;28(1):77–85.
3. Berman JD, Ebisu K, Peng RD, et al. Drought and the risk of hospital admissions and mortality in older adults in western USA from 2000 to 2013: A retrospective study. *The Lancet Planetary Health*. 2017;1(1):e17–e25.
4. Bobb JF, Ho KK, Yeh RW, et al. Time-course of cause-specific hospital admissions during snowstorms: An analysis of electronic medical records from major hospitals in Boston, Massachusetts. *American Journal of Epidemiology*. 2017;185(4):283–294.
5. Grimes DA, Schulz KF. Bias and causal associations in observational research. *The Lancet*. 2002;359(9302):248–252.
6. Liu J, Wang S-Y. Analysis of human vulnerability to the extreme rainfall event on 21–22 July 2012 in Beijing, China. *Natural Hazards and Earth System Sciences*. 2013;13(11):2911–2926.
7. Jin MS, Li Y, Su D. Urban-induced mechanisms for an extreme rainfall event in Beijing China: A satellite perspective. *Climate*. 2015;3(1):193–209.
8. Moore TW, Dixon RW. Climatology of tornadoes associated with Gulf Coast-landfalling hurricanes. *Geographical Review*. 2011;101(3):371–395.
9. Brunkard J, Namulanda G, Ratard R. Hurricane Katrina deaths, Louisiana, 2005. *Disaster Medicine and Public Health Preparedness*. 2008;2(4):215–223.
10. Klinger C, Owen Landeg VM. Power outages, extreme events and health: A systematic review of the literature from 2011–2012. *PLoS Currents*. 2014;6.
11. Shultz JM, Galea S. Preparing for the next Harvey, Irma, or Maria—addressing research gaps. *New England Journal of Medicine*. 2017;377(19):1804–1806.
12. Caillouët KA, Michaels SR, Xiong X, et al. Increase in West Nile neuroinvasive disease after Hurricane Katrina. *Emerging Infectious Diseases*. 2008;14(5):804.
13. Anderson GB, Bell ML. Heat waves in the United States: Mortality risk during heat waves and effect modification by heat wave characteristics in 43 US communities. *Environmental Health Perspectives*. 2011;119(2):210.
14. Gasparrini A, Guo Y, Hashizume M, et al. Mortality risk attributable to high and low ambient temperature: A multicountry observational study. *The Lancet*. 2015;386(9991):369–375.
15. Kishore N, Marques D, Mahmud A, et al. Mortality in Puerto Rico after Hurricane Maria. *New England Journal of Medicine* [electronic article]. 2018;(https://doi.org/10.1056/NEJMsa1803972)
16. Kelman J, Finne K, Bogdanov A, et al. Dialysis care and death following Hurricane Sandy. *American Journal of Kidney Diseases*. 2015;65(1):109–115.
17. Kessler RC, Group HKCA, others. Hurricane Katrina's impact on the care of survivors with chronic medical conditions. *Journal of General Internal Medicine*. 2007;22(9):1225–1230.
18. Howard D, Zhang R, Huang Y, et al. Hospitalization rates among dialysis patients during Hurricane Katrina. *Prehospital and Disaster Medicine*. 2012;27(4):325–329.
19. Atef M, Nadjatfl I, Boroumand B, et al. Acute renal failure in earthquake victims in Iran: Epidemiology and management. *QJM: An International Journal of Medicine*. 1994;87(1):35–40.
20. Oda J, Tanaka H, Yoshioka T, et al. Analysis of 372 patients with crush syndrome caused by the Hanshin-Awaji earthquake. *Journal of Trauma and Acute Care Surgery*. 1997;42(3):470–476.
21. Ferdinand KC. The Hurricane Katrina disaster: Focus on the hypertensive patient. *The Journal of Clinical Hypertension*. 2005;7(11):679–680.

22. Fonseca VA, Smith H, Kuhadiya N, et al. Impact of a natural disaster on diabetes: Exacerbation of disparities and long-term consequences. *Diabetes Care*. 2009;
23. Twombly R. Cancer community offers unprecedented support after Hurricanes Slam US Gulf Coast. *Journal of the National Cancer Institute*. 2005;97(23):1716–1718.
24. Loehn B, Pou AM, Nuss DW, et al. Factors affecting access to head and neck cancer care after a natural disaster: A post–Hurricane Katrina survey. *Head & Neck*. 2011;33(1):37–44.
25. Cefalu WT, Smith SR, Blonde L, et al. The Hurricane Katrina aftermath and its impact on diabetes care: Observations from "Ground Zero": Lessons in disaster preparedness of people with diabetes. *Diabetes Care*. 2006;29(1):158–160.
26. Knutson TR, McBride JL, Chan J, et al. Tropical cyclones and climate change. *Nature Geoscience*. 2010;3(3):157.
27. Knutson TR, Sirutis JJ, Zhao M, et al. Global projections of intense tropical cyclone activity for the late twenty-first century from dynamical downscaling of CMIP5/RCP4.5 scenarios. *Journal of Climate*. 2015;28(18):7203–7224.
28. Bender MA, Knutson TR, Tuleya RE, et al. Modeled impact of anthropogenic warming on the frequency of intense Atlantic hurricanes. *Science*. 2010;327(5964):454–458.
29. Zane DF, Bayleyegn TM, Hellsten J, et al. Tracking deaths related to Hurricane Ike, Texas, 2008. *Disaster Medicine and Public Health Preparedness*. 2011;5(1):23–28.
30. Choudhary E, Zane DF, Beasley C, et al. Evaluation of active mortality surveillance system data for monitoring hurricane-related deaths—Texas, 2008. *Prehospital and Disaster Medicine*. 2012;27(4):392–397.
31. McKinney N, Houser C, Meyer-Arendt K. Direct and indirect mortality in Florida during the 2004 hurricane season. *International Journal of Biometeorology*. 2011;55(4):533–546.
32. Santos-Burgoa C, Goldman A, Andrade E, et al. Ascertainment of the estimated excess mortality from Hurricane Maria in Puerto Rico. 2018;
33. Robles F, Davis K, Almukhtar S. Official Toll in Puerto Rico: 64. Actual Deaths May Be 1,052. 2017;(https://www.nytimes.com/interactive/2017/12/08/us/puerto-rico-hurricane-maria-death-toll.html)
34. Rivera R, Rolke W. Estimating the death toll of Hurricane Maria. *Significance*. 2018;15(1):8–9.
35. Santos-Lozada AR, Howard JT. Use of death counts from vital statistics to calculate excess deaths in Puerto Rico following Hurricane Maria. *Journal of the American Medical Association*. 2018;
36. Centers for Disease Control and Prevention. A reference guide for certification of deaths in the event of a natural, human-induced, or chemical/radiological disaster. *NVSS: National Vital Statistics System* [electronic article]. 2017;(1). (https://www.cdc.gov/nchs/nvss/reporting-guidance.htm)
37. Simms E, Miller K, Stanbury M, et al. Disaster Surveillance Capacity in the United States: Results from a 2012 CSTE Assessment, Council of State and Territorial Epidemiologists. 2014;(https://c.ymcdn.com/sites/www.cste.org/resource/resmgr/EnvironmentalHealth/Disaster_Epi_Baseline731KM.pdf)
38. Kleinpeter MA. Disaster preparedness for dialysis patients. *Clinical Journal of the American Society of Nephrology*. 2011;6(10):2337–2339.
39. Lempert KD, Kopp JB. Hurricane Sandy as a kidney failure disaster. *American Journal of Kidney Diseases: the Official Journal of the National Kidney Foundation*. 2013;61(6):865.
40. Kleinpeter MA, Norman LD, Krane NK. Disaster planning for peritoneal dialysis programs. *Advances in Peritoneal Dialysis*. 2006;22:124.
41. Sharma AJ, Weiss EC, Young SL, et al. Chronic disease and related conditions at emergency treatment facilities in the New Orleans area after Hurricane Katrina. *Disaster Medicine and Public Health Preparedness*. 2008;2(1):27–32.
42. Berg B van den, Grievink L, Yzermans J, et al. Medically unexplained physical symptoms in the aftermath of disasters. *Epidemiologic Reviews*. 2005;27(1):92–106.

Appendix A: Supplemental material for Chapter 2

1. Supplemental methods

We calculated confidence interval for the estimate of total excess deaths on July 21–22, 2012 (results shown in Table 2.1 in Chapter 2) through Monte Carlo simulations. First, we took 5,000 random samples of $\boldsymbol{\beta}_l$, for $l = 0$ and 1, from the assumed multivariate normal distribution ($N_2(\boldsymbol{\mu}, \boldsymbol{\Sigma})$), with the mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$ resulting from fitting eq. 2.1 in the main text to the observed mortality data from Beijing. We then used each of these samples to calculate an estimate of excess deaths on the peak flood day (July 21, 2012) and the following day (July 22, 2012), using eq. 2.2 in Chapter 2, and added up the excess deaths on these two days for each sample. The 2.5 and 97.5 percentiles of the distribution of these 5,000 estimates can be interpreted as a 95% empirical confidence interval for the estimate of total excess deaths on July 21–22, 2012.

2. Supplemental results

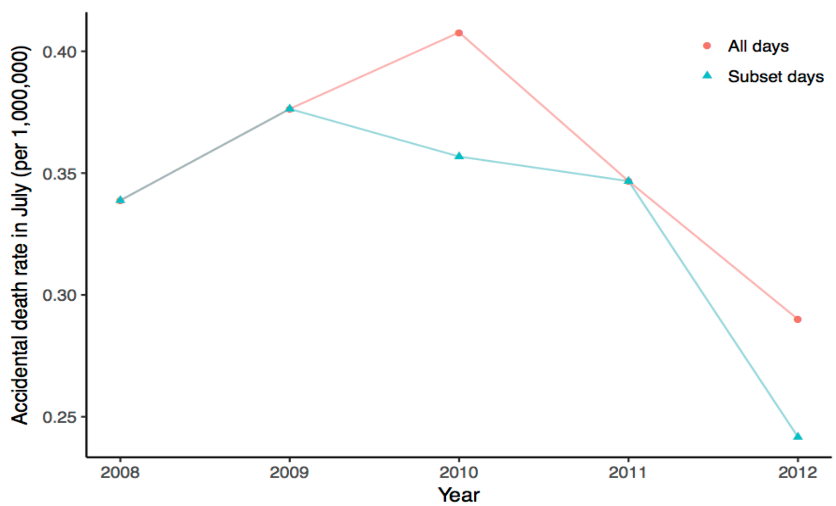

Figure A1 Accidental mortality rate in July in Beijing per 1,000,000 residents by study year. The red points and line ('All days') show rates calculated based on all the days in July. The blue points and line ('Subset days') show rates calculated after excluding data from July 21–22, 2012, and days with temperature greater than 90th percentile of July.

Appendix B: Supplemental material for Chapter 3

1. Supplemental methods of estimating lag-specific relative risk for ten most severe wind-based storms

We estimated the lag-specific relative risk for ten most severe wind-based storms for all-cause and cardiovascular mortality. For each storm and its affected community, we fit the following generalized linear fixed-effect model with an unconstrained distributed lag function of storm exposure to the single-community, single-storm matched data:

$$\log[E(Y_t)] = \log(n) + \alpha + \sum_{l=-2}^{7} \beta_l x_{t+l} + \delta Year_t + \boldsymbol{\gamma} DOW_t \qquad \text{(B1)}$$

where:

- Y_t is the mortality counts on day *t*;
- n is the residents' population;
- α is the model intercept;
- $\sum_{l=-2}^{7} \beta_l x_{t+l}$ is an unconstrained distributed lag function of storm exposure variable *x*. β_l is the coefficient estimating the association between tropical cyclone exposure and mortality at lag *l* from day *t*, the day of the storm's closest approach to study community. x_{t+l} is the indicator variable representing whether a given day at lag *l* from day *t* is part of an exposed storm period or part of a matched unexposed period.
- $Year_t$ is the year of day *t* and δ is the regression coefficient for $Year$, to account for a linear trend in mortality rate across year;
- DOW_t is an indicator variable for day of week on day *t*, and $\boldsymbol{\gamma}$ is a vector of regression coefficients for DOW.

We calculated the RRs of each of the ten most severe wind-based storms, separately. Results are shown in Figure B2 and B3.

2. Supplemental results

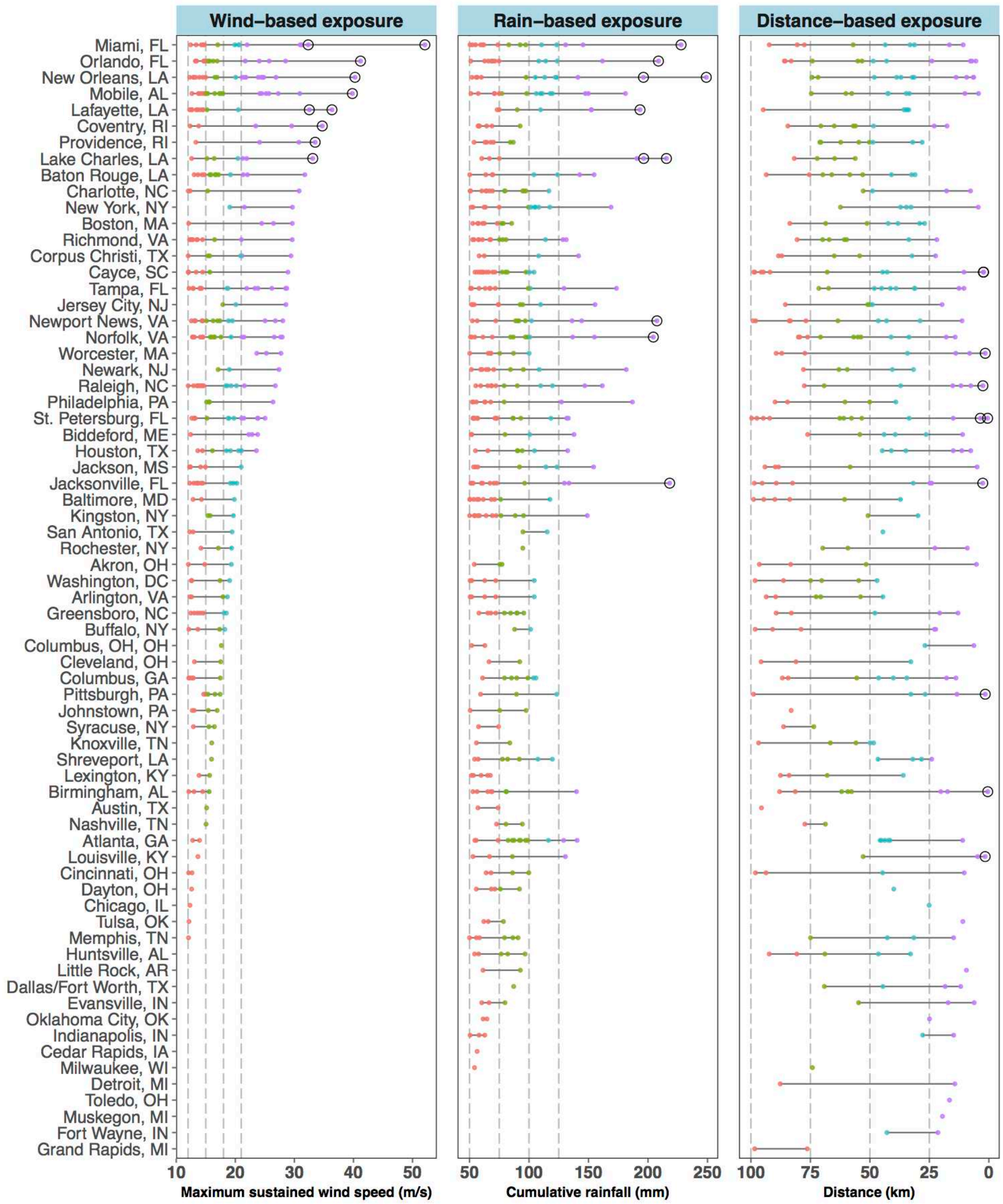

Figure B1 Community-specific exposures to Atlantic-basin tropical cyclones, 1988-2005, for the three continuous exposure metrics considered. Each point shows a tropical cyclone exposure within the community listed on the left axis, with the continuous value for the exposure metric shown on the x-axis. For communities with multiple storm exposures under a given exposure metric, a line is used to show the range of exposure severities across storms. For these three continuous metrics, multiple thresholds were considered in assessing binary storm exposure for our analysis; color is used to highlight these different thresholds, from least severe (red) to most severe (purple). Note that the scale of the x-axis for distance (right panel) is reversed, reflecting that storms that came closer to the community (smaller distance) represent a more severe exposure. The ten most notable community storm exposure for each exposure metric over our study period are highlighted by black circles.

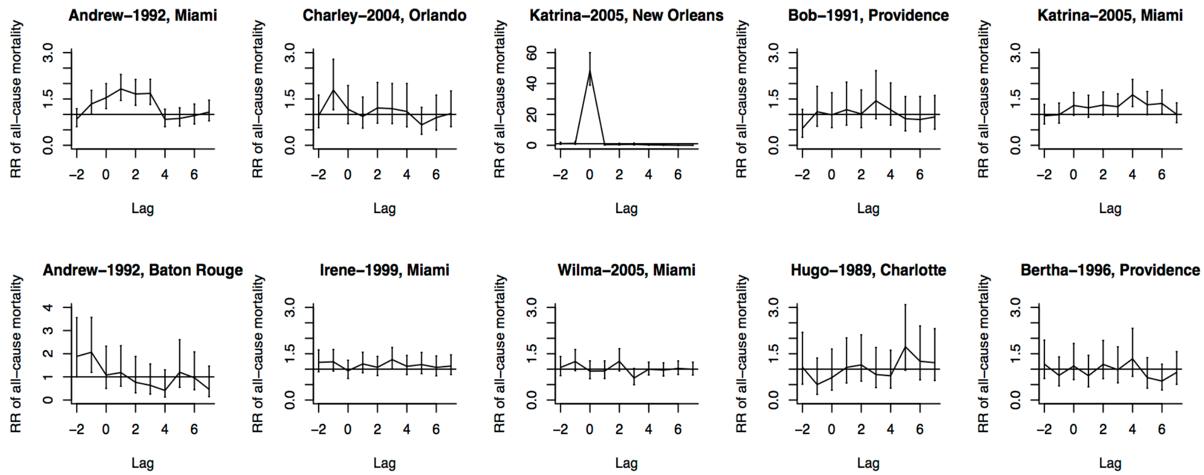

Figure B2 Estimates of lag-specific relative risk of all-cause mortality on days during storm periods compared to matched days in non-storm periods, for most severe wind-based storm exposures among communities with population greater than 400,000.

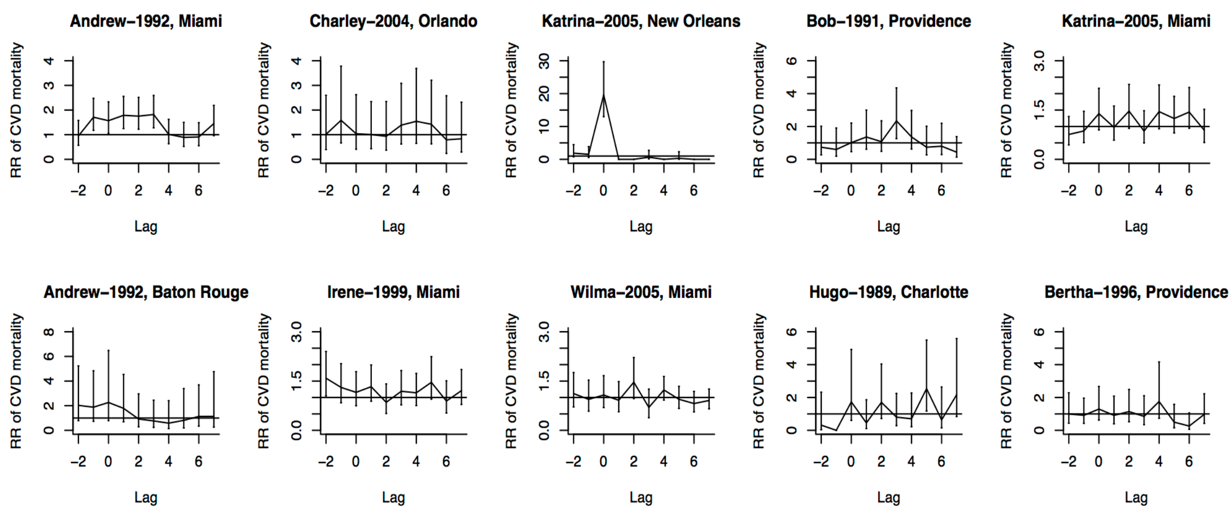

Figure B3 Estimates of lag-specific relative risk of cardiovascular mortality on days during storm periods compared to matched days in non-storm periods, for most severe wind-based storm exposures among communities with population greater than 400,000.

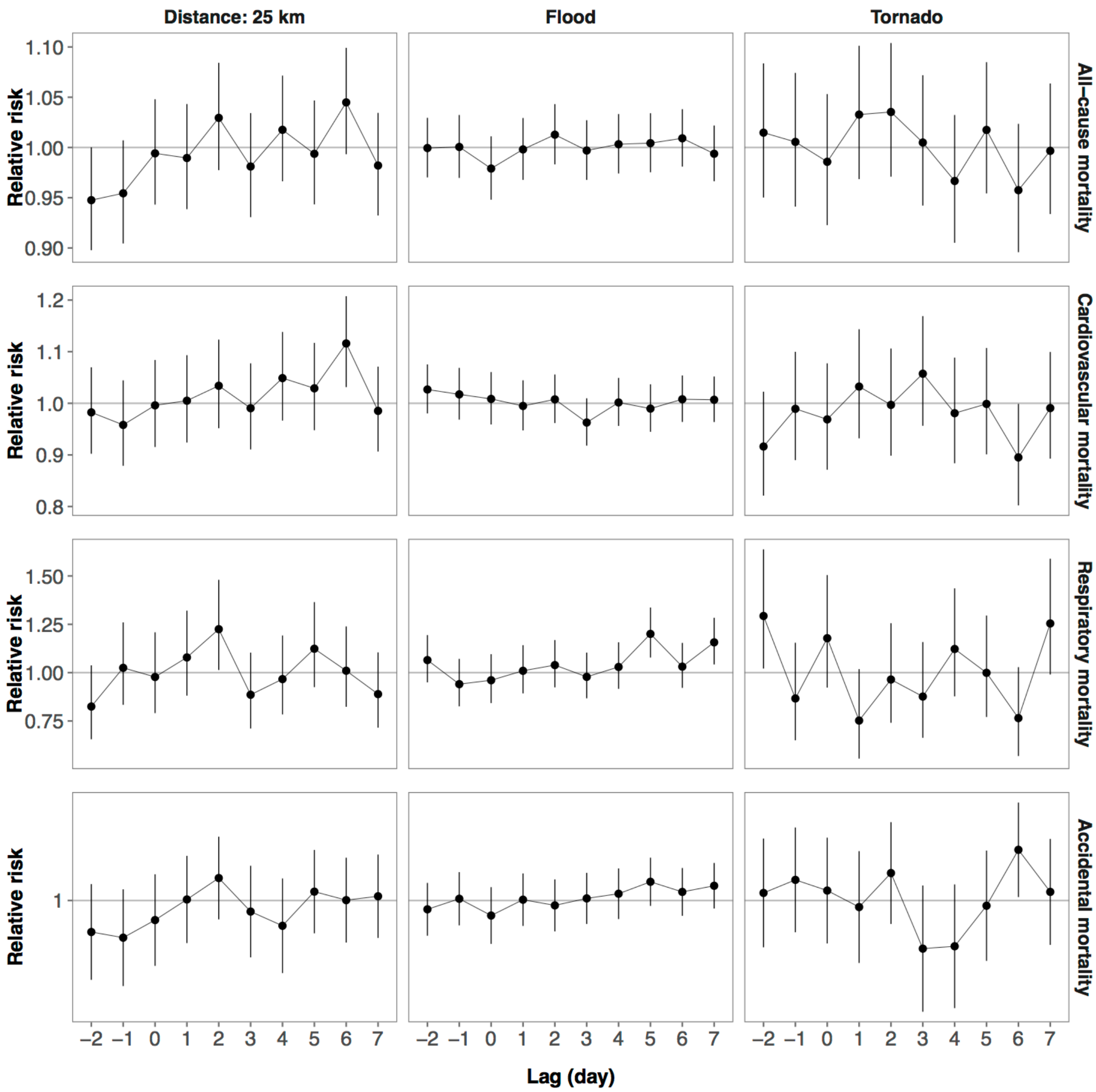

Figure B4 Estimates of lag-specific relative risk of tropical cyclone exposures on mortality on days during storm periods compared to matched days in non-storm periods, for all storms and across all exposed communities, based on the strictest storm exposure definitions considered for distance-based exposure metric, as well as flood- and tornado-based metrics.

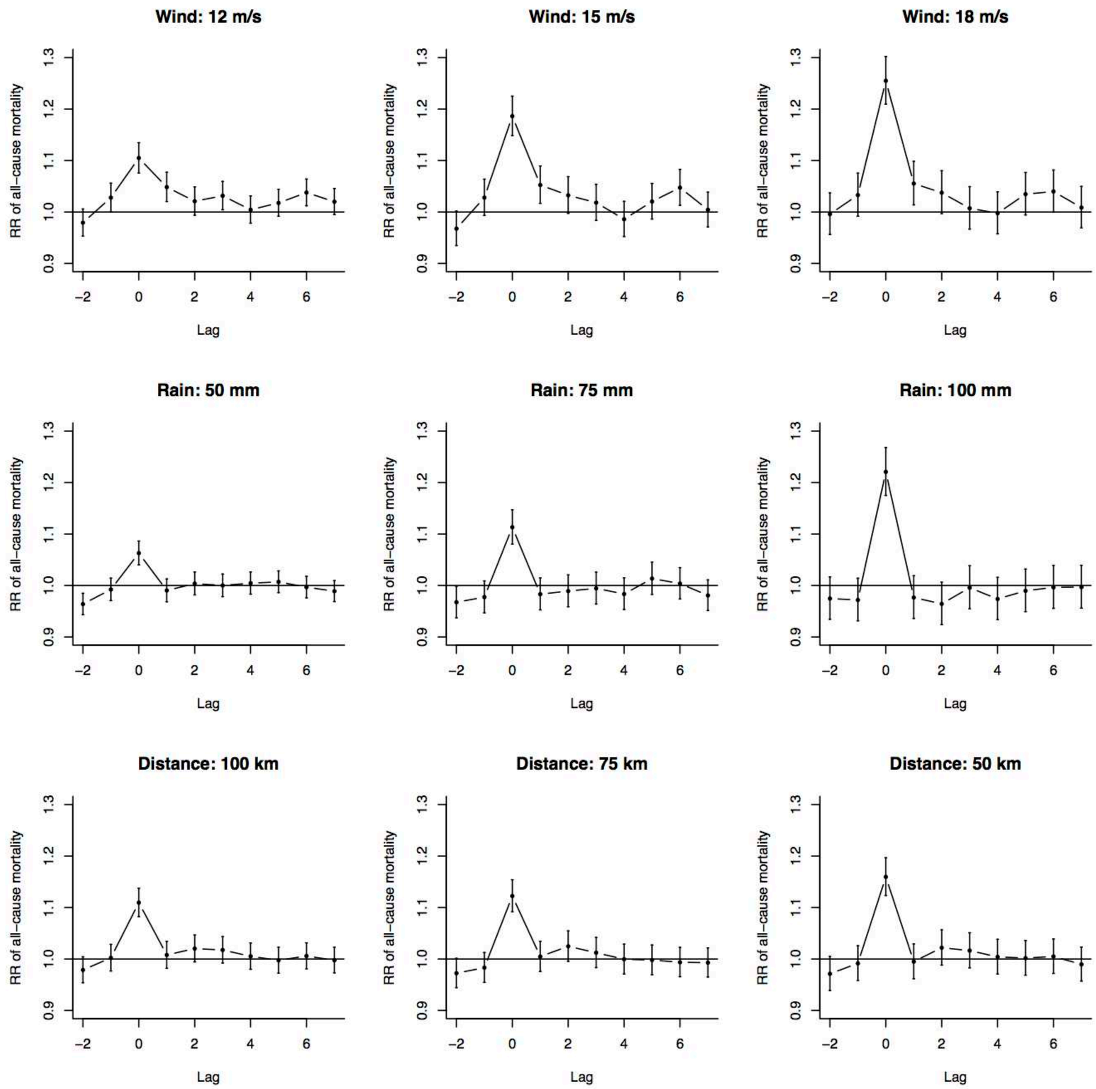

Figure B5 Estimates of lag-specific relative risk of tropical cyclone exposures on **all-cause mortality** on days during storm periods compared to matched days in non-storm periods, for all storms and across all exposed communities, based on more lenient thresholds for the three continuous exposure metrics considered (wind, distance, and rain).

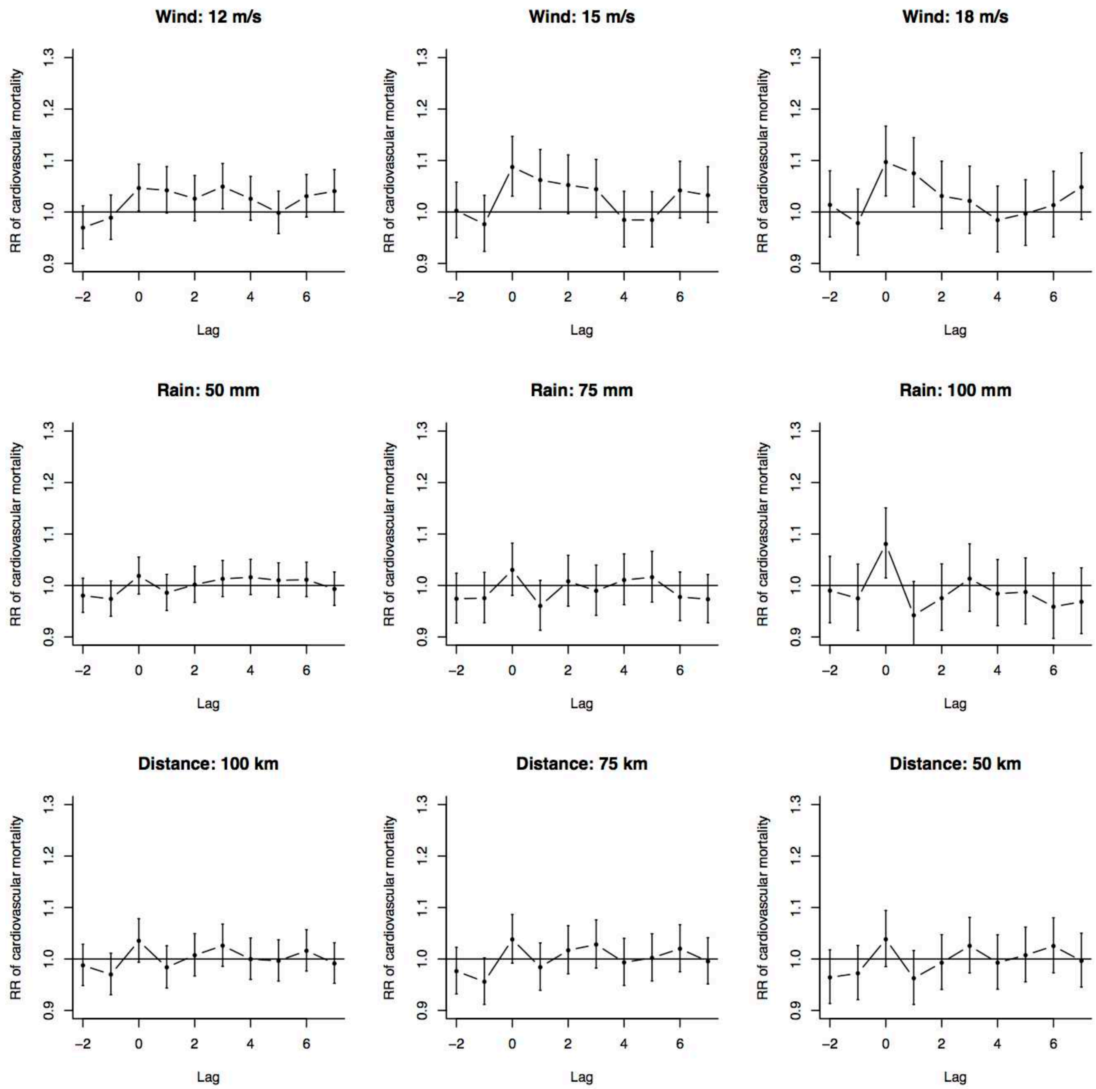

Figure B6 Estimates of lag-specific relative risk of tropical cyclone exposures on **cardiovascular mortality** on days during storm periods compared to matched days in non-storm periods, for all storms and across all exposed communities, based on more lenient thresholds for the three continuous exposure metrics considered (wind, distance, and rain).

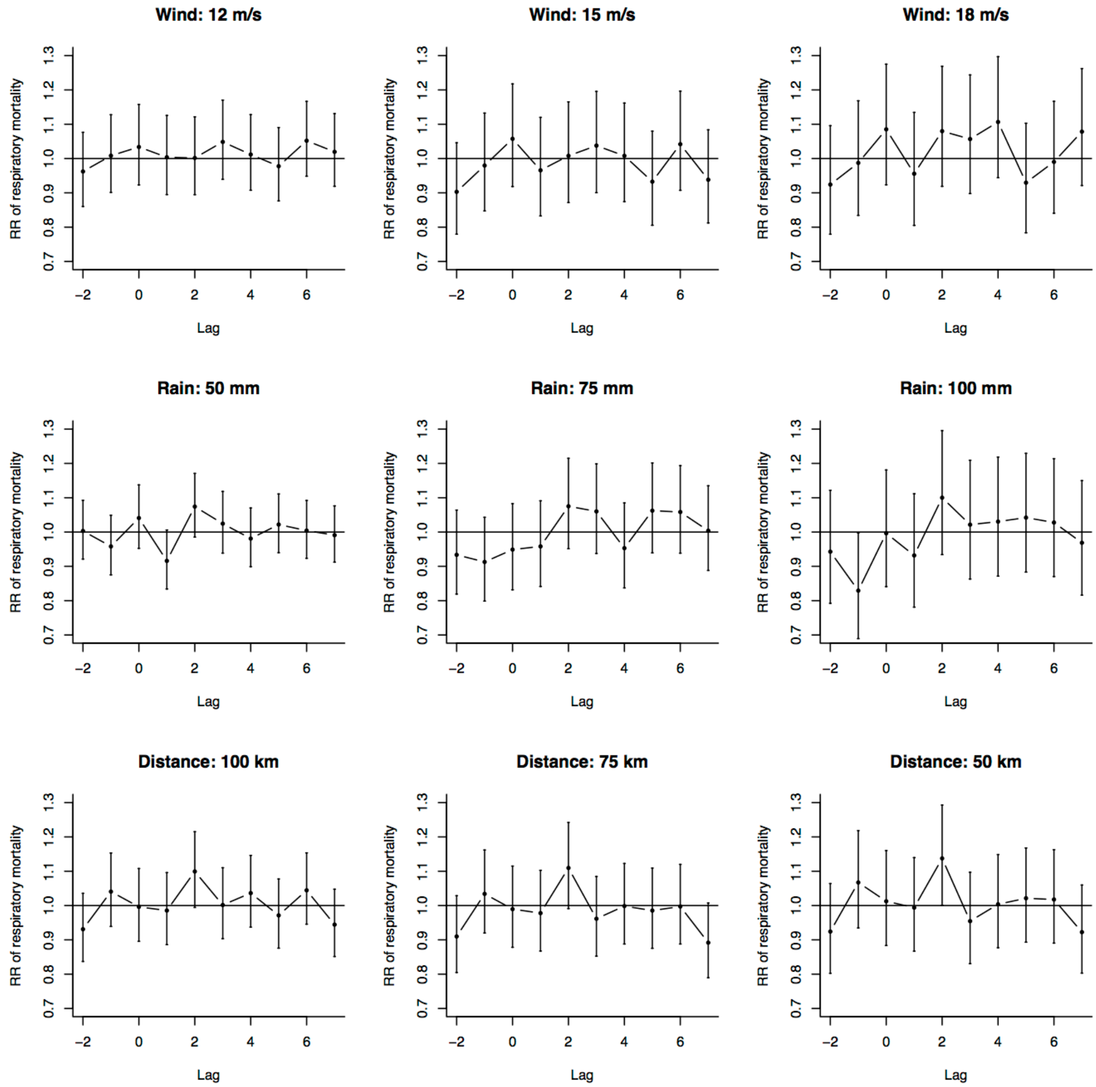

Figure B7 Estimates of lag-specific relative risk of tropical cyclone exposures on **respiratory mortality** on days during storm periods compared to matched days in non-storm periods, for all storms and across all exposed communities, based on more lenient thresholds for the three continuous exposure metrics considered (wind, distance, and rain).

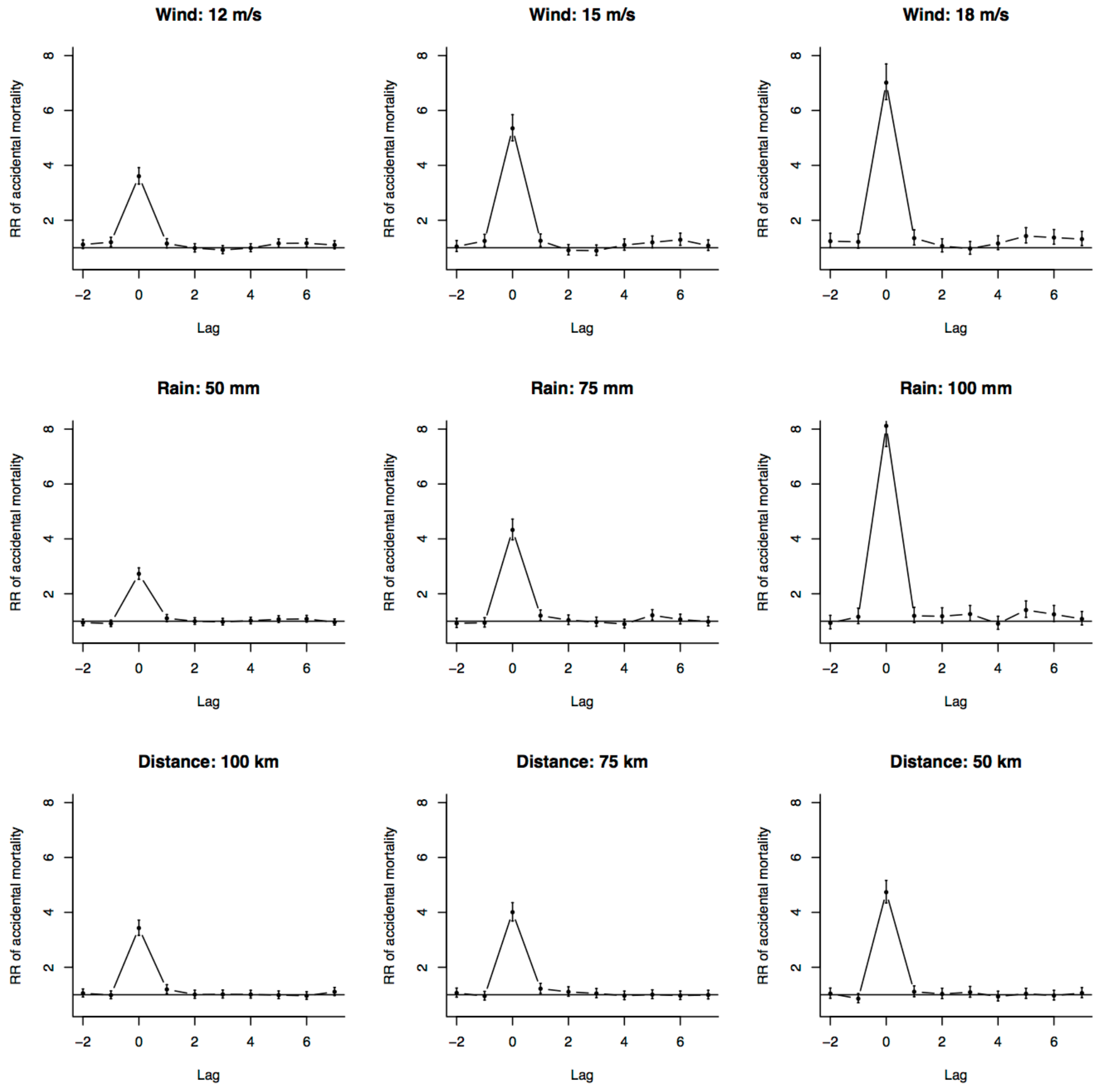

Figure B8 Estimates of lag-specific relative risk of tropical cyclone exposures on **accidental mortality** on days during storm periods compared to matched days in non-storm periods, for all storms and across all exposed communities, based on more lenient thresholds for the three continuous exposure metrics considered (wind, distance, and rain).

Table B1 Relative risk (RR) at lag 0 and cumulative RR for all storms and across all exposed large-population communities, as well as RRs for all other storms and across all exposed large population communities, excluding the ten most severe wind-based storm exposures.

	Same day RR*	Cumulative RR#
All-cause mortality		
All storms	1.42 (1.36, 1.49)	1.90 (1.58, 2.29)
All other storms	1.00 (0.95, 1.06)	1.18 (0.96, 1.45)
Cardiovascular mortality		
All storms	1.15 (1.06, 1.24)	1.30 (0.97, 1.76)
All other storms	1.01 (0.92, 1.10)	1.03 (0.74, 1.43)
Respiratory mortality		
All storms	1.13 (0.92, 1.38)	1.54 (0.70, 3.39)
All other storms	1.06 (0.85, 1.33)	1.30 (0.54, 3.09)
Accidental mortality		
All storms	12.03 (10.87, 13.32)	161.40 (61.62, 422.75)
All other storms	0.73 (0.51, 1.06)	1.37 (0.41, 4.54)

*Estimate of RR on the day of storm's closest approach (lag 0).
#Estimate of cumulative RR across the full storm periods.

Table B2 Estimates of lag-specific relative risk (shown in Figure 3.2 in Chapter 3) of mortality on days during storm periods compared to matched days in non-storm periods, across all tropical cyclone exposures for study storms and study communities, based on the strictest thresholds for wind- and rain-based exposure metrics.

Lag	All-cause mortality	Cardiovascular mortality	Respiratory mortality	Accidental mortality
Wind: 21 m/s				
-2	1.01 (0.96, 1.07)	1.03 (0.95, 1.12)	1.04 (0.84, 1.29)	1.34 (1.01, 1.78)
-1	1.05 (0.99, 1.10)	0.98 (0.90, 1.07)	0.99 (0.79, 1.23)	1.45 (1.11, 1.90)
0	1.42 (1.36, 1.49)	1.15 (1.06, 1.24)	1.13 (0.92, 1.38)	12.03 (10.87, 13.32)
1	1.04 (0.99, 1.10)	1.04 (0.96, 1.13)	0.92 (0.73, 1.16)	1.59 (1.23, 2.06)
2	1.07 (1.01, 1.12)	1.04 (0.96, 1.13)	1.08 (0.88, 1.34)	1.29 (0.97, 1.71)
3	1.05 (1.00, 1.11)	1.04 (0.96, 1.13)	1.05 (0.85, 1.30)	1.22 (0.91, 1.63)
4	1.00 (0.95, 1.05)	0.97 (0.90, 1.06)	1.23 (1.01, 1.50)	0.97 (0.70, 1.33)
5	1.02 (0.97, 1.07)	0.98 (0.91, 1.07)	0.91 (0.73, 1.14)	1.30 (0.98, 1.73)
6	1.03 (0.97, 1.08)	0.97 (0.90, 1.06)	1.00 (0.81, 1.24)	1.39 (1.05, 1.82)
7	1.03 (0.98, 1.08)	1.07 (0.99, 1.15)	1.12 (0.91, 1.37)	1.57 (1.23, 2.01)
Rain: 125 mm				
-2	1.02 (0.95, 1.09)	1.05 (0.94, 1.17)	0.90 (0.66, 1.23)	1.01 (0.66, 1.56)
-1	1.04 (0.97, 1.12)	1.07 (0.95, 1.19)	0.86 (0.63, 1.18)	1.46 (0.98, 2.15)
0	1.69 (1.60, 1.79)	1.30 (1.18, 1.44)	0.91 (0.67, 1.23)	22.53 (20.03, 25.35)
1	1.05 (0.97, 1.12)	1.01 (0.90, 1.13)	0.83 (0.60, 1.14)	1.54 (1.07, 2.22)
2	1.03 (0.96, 1.11)	0.96 (0.86, 1.08)	1.22 (0.93, 1.59)	1.98 (1.42, 2.76)
3	1.05 (0.98, 1.13)	1.08 (0.97, 1.20)	0.99 (0.74, 1.33)	1.86 (1.34, 2.58)
4	1.00 (0.93, 1.07)	0.98 (0.88, 1.10)	1.20 (0.91, 1.58)	1.05 (0.69, 1.61)
5	1.04 (0.97, 1.12)	1.01 (0.90, 1.13)	0.98 (0.73, 1.33)	1.54 (1.08, 2.20)
6	1.06 (0.99, 1.13)	0.98 (0.88, 1.10)	1.11 (0.84, 1.47)	1.57 (1.07, 2.29)
7	1.04 (0.97, 1.11)	1.00 (0.89, 1.12)	1.01 (0.76, 1.35)	2.00 (1.46, 2.75)

Table B3 Estimates of cumulative relative risk (shown in Figure 3.3 in Chapter 3) of tropical cyclone exposures on mortality across the full storm period considered (two days before to seven days after the date of storm's closest approach to the community) compared to matched non-storm periods.

Exposure	All-cause mortality	Cardiovascular mortality	Respiratory mortality	Accidental mortality
Wind: 12 m/s	1.33 (1.22, 1.45)	1.24 (1.07, 1.42)	1.12 (0.77, 1.63)	7.41 (4.64, 11.84)
Wind: 15 m/s	1.38 (1.23, 1.55)	1.30 (1.08, 1.56)	0.87 (0.53, 1.43)	12.89 (6.97,
Wind: 18 m/s	1.54 (1.34, 1.77)	1.28 (1.03, 1.60)	1.19 (0.66, 2.12)	43.31 (21.33,
Wind: 21 m/s	1.90 (1.58, 2.29)	1.30 (0.97, 1.76)	1.54 (0.70, 3.39)	161.40 (61.62,
Rain: 50 mm	1.01 (0.94, 1.08)	1.00 (0.89, 1.13)	1.01 (0.75, 1.35)	2.93 (1.98, 4.33)
Rain: 75 mm	1.00 (0.90, 1.11)	0.92 (0.77, 1.09)	0.95 (0.61, 1.47)	5.24 (3.02, 9.10)
Rain: 100 mm	1.04 (0.89, 1.21)	0.88 (0.69, 1.12)	0.87 (0.45, 1.68)	27.41 (12.25,
Rain: 125 mm	2.34 (1.79, 3.07)	1.48 (0.95, 2.30)	0.94 (0.29, 3.05)	955.40 (256.39,
Distance: 100 km	1.15 (1.05, 1.25)	1.01 (0.88, 1.16)	1.04 (0.73, 1.48)	4.63 (2.92, 7.33)
Distance: 75 km	1.10 (1.00, 1.21)	1.01 (0.86, 1.18)	0.85 (0.57, 1.27)	5.33 (3.18, 8.93)
Distance: 50 km	1.15 (1.03, 1.29)	0.97 (0.81, 1.17)	1.04 (0.65, 1.64)	5.24 (2.90, 9.50)
Distance: 25 km	0.93 (0.78, 1.12)	1.15 (0.86, 1.52)	0.94 (0.46, 1.93)	0.57 (0.22, 1.52)
Flood	1.00 (0.90, 1.10)	1.02 (0.87, 1.20)	1.46 (0.98, 2.17)	1.17 (0.68, 2.00)
Tornado	1.01 (0.81, 1.27)	0.83 (0.57, 1.20)	0.90 (0.36, 2.26)	1.13 (0.34, 3.76)

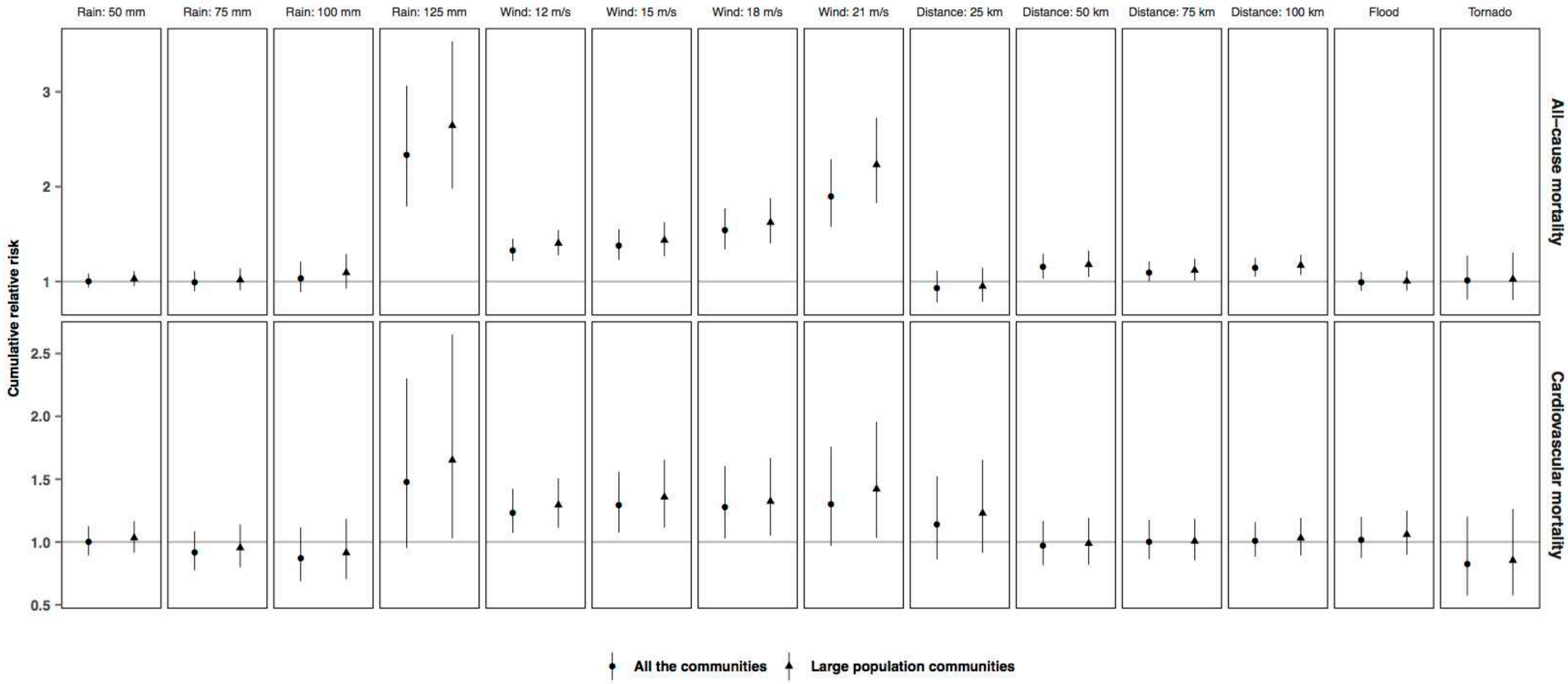

Figure B9 Estimates of cumulative relative risk of tropical cyclone exposures on all-cause and cardiovascular mortality in all exposed communities (circle) and when analysis is restricted to the subset of large communities (population > 400,000) used in the main results for the analysis of respiratory and accidental mortality (triangle).

Appendix C: Supplemental material for Chapter 4

1. Supplemental methods of estimating lag-specific relative risk for ten most severe wind-based storms

We estimated the lag-specific relative risk for ten most severe wind-based storms for emergency hospital admissions. For each storm and its affected county, we fit the following generalized linear fixed-effect model with unconstrained distributed lag function of storm exposure, to the single-county, single-storm matched data:

$$\log[E(Y_t)] = \log(n) + \alpha + \sum_{l=-2}^{7} \beta_l x_{t+l} + \delta Year_t + \boldsymbol{\gamma} DOW_t \qquad \text{(C1)}$$

where:

- Y_t is the mortality counts on day *t*;
- n is the total number of Medicare beneficiaries residing in a certain county on day *t*, included as an offset term;
- α is the model intercept;
- $\sum_{l=-2}^{7} \beta_l x_{t+l}$ is an unconstrained distributed lag function of storm exposure variable *x*. β_l is the coefficient estimating the association between tropical cyclone exposure and hospital admissions at lag *l* from day *t*, the day of the storm's closest approach to study county. x_{t+l} is the indicator variable representing whether a given day at lag *l* from day *t* is part of an exposed storm period or part of a matched unexposed period.
- $Year_t$ is the year of day *t* and δ is the regression coefficient for $Year$, to account for a linear trend in mortality rate across year;
- DOW_t is an indicator variable for day of week on day *t*, and $\boldsymbol{\gamma}$ is a vector of regression coefficients for DOW.

We calculated the RRs of each of the ten most severe wind-based storms, among all the study counties and out-of-Florida counties. Results are shown in Figure C2–C5.

2. Supplemental results

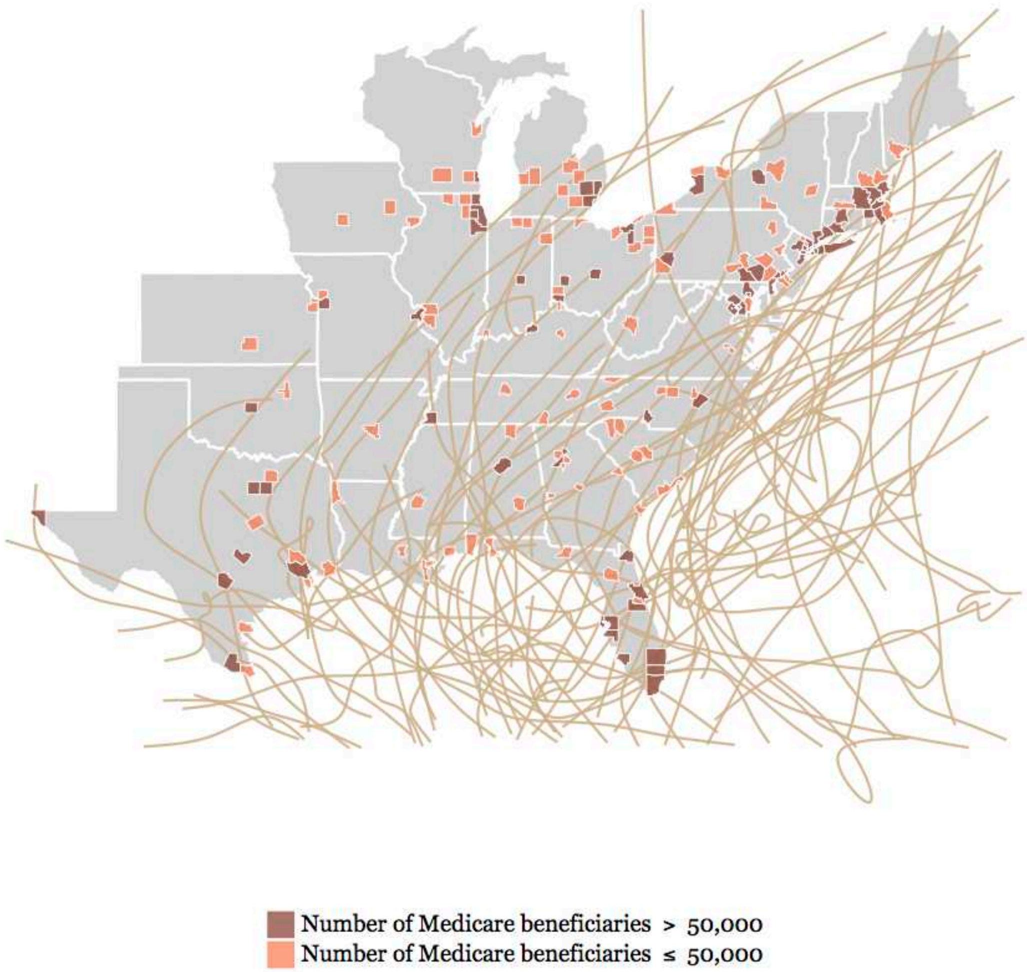

Figure C1 Map counties with total number of Medicare beneficiaries greater than 50000 on the day of tropical cyclone's closest approach to the county.

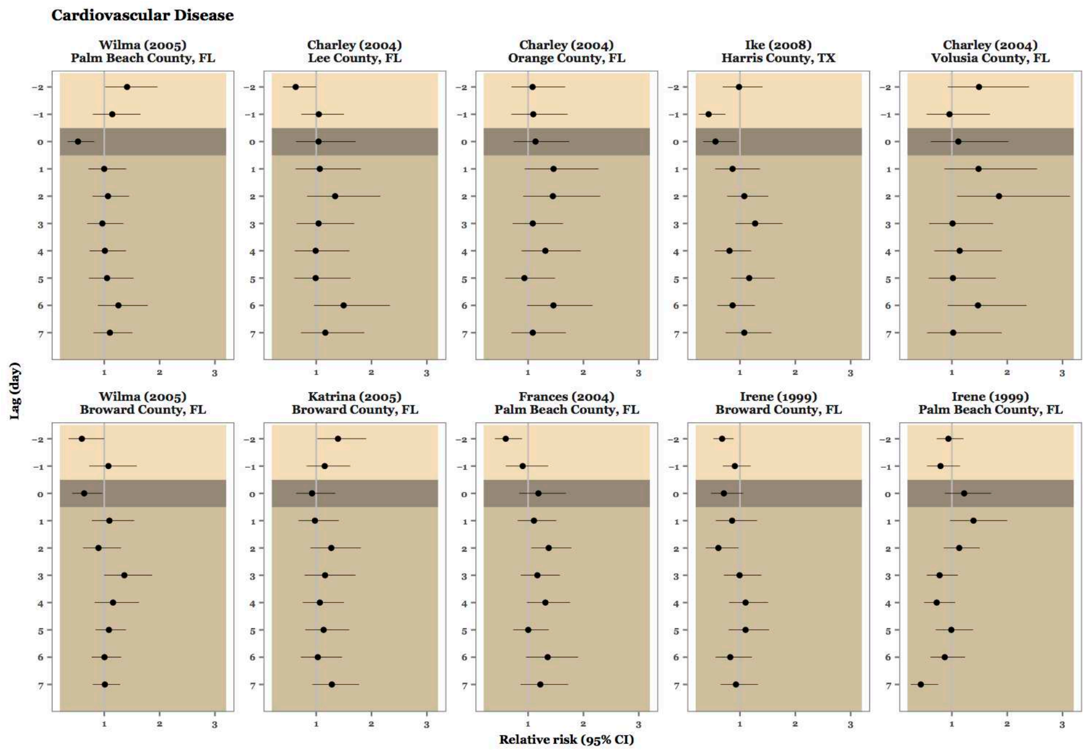

Figure C2 Estimates of distributed relative risks of cardiovascular disease hospitalizations for the ten most severe wind-based tropical cyclones, among counties with total number of Medicare beneficiaries greater than 50,000.

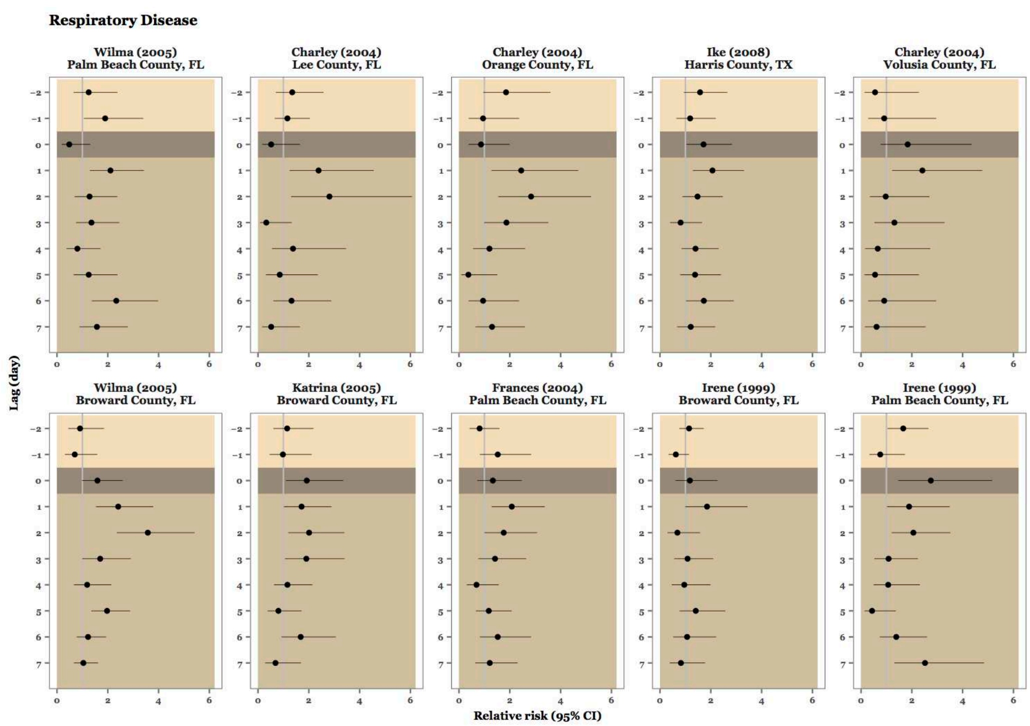

Figure C3 Estimates of distributed relative risks of respiratory disease hospitalizations for the ten most severe wind-based tropical cyclones, among counties with total number of Medicare beneficiaries greater than 50,000

Table C1 Estimates of relative risk and attributable number of hospitalizations of ten most notable wind-based storms among out-of-Florida counties with total number of Medicare beneficiaries greater than 50,000*

				Cardiovascular disease		Respiratory disease	
Tropical cyclone	County	Date	Wind (m/s)	RR	Attributable number	RR	Attributable number
Same day estimates#							
Ike (2008)	Harris County, TX	2008-09-13	38.7	0.47 (0.18, 1.26)	-17 (-70, 3)	1.25 (0.58, 2.69)	3 (-12, 11)
Floyd (1999)	Suffolk County, MA	1999-09-17	24.5	0.66 (0.16, 2.70)	-6 (-64, 8)	0.74 (0.05, 11.06)	-2 (-134, 6)
Floyd (1999)	Norfolk County, MA	1999-09-17	24.4	1.30 (0.59, 2.86)	4 (-10, 10)	1.09 (0.17, 7.22)	0 (-10, 2)
Floyd (1999)	Suffolk County, NY	1999-09-16	24.3	1.00 (0.61, 1.66)	0 (-18, 11)	1.94 (0.37, 10.27)	3 (-12, 6)
Floyd (1999)	Essex County, MA	1999-09-17	24.2	0.51 (0.11, 2.37)	-19 (-162, 12)	1.06 (0.20, 5.69)	0 (-21, 4)
Floyd (1999)	Middlesex County, MA	1999-09-17	24.1	1.58 (0.75, 3.35)	8 (-7, 15)	0.14 (0.05, 0.40)	-38 (-122, -9)
Floyd (1999)	Providence County, RI	1999-09-17	24.1	0.99 (0.41, 2.40)	0 (-1, 1)	0.21 (0.01, 3.48)	-8 (-163, 1)
Ike (2008)	Marion County, IN	2008-09-14	23.2	0.85 (0.37, 1.94)	-2 (-18, 5)	1.10 (0.25, 4.89)	1 (-18, 5)
Ike (2008)	Wayne County, MI	2008-09-14	23.1	0.93 (0.52, 1.66)	-4 (-45, 19)	1.15 (0.71, 1.86)	2 (-5, 6)
Floyd (1999)	Nassau County, NY	1999-09-16	22.8	1.60 (1.14, 2.25)	7 (2, 11)	1.40 (0.26, 7.44)	1 (-8, 3)
Cumulative estimates&							
Ike (2008)	Harris County, TX	2008-09-13	38.7	0.93 (0.78, 1.10)	-21 (-76, 25)	1.44 (1.25, 1.65)	45 (30, 58)
Floyd (1999)	Suffolk County, MA	1999-09-17	24.5	1.27 (1.01, 1.58)	23 (2, 41)	1.22 (0.79, 1.89)	7 (-11, 19)
Floyd (1999)	Norfolk County, MA	1999-09-17	24.4	0.88 (0.66, 1.16)	-18 (-64, 17)	0.78 (0.55, 1.08)	-13 (-36, 3)
Floyd (1999)	Suffolk County, NY	1999-09-16	24.3	0.98 (0.83, 1.16)	-6 (-58, 39)	1.14 (0.93, 1.39)	11 (-7, 25)
Floyd (1999)	Essex County, MA	1999-09-17	24.2	0.84 (0.57, 1.24)	-29 (-114, 28)	0.94 (0.62, 1.45)	-2 (-23, 11)
Floyd (1999)	Middlesex County, MA	1999-09-17	24.1	1.05 (0.90, 1.23)	12 (-29, 46)	1.07 (0.81, 1.40)	6 (-22, 28)
Floyd (1999)	Providence County, RI	1999-09-17	24.1	1.05 (0.82, 1.35)	3 (-14, 17)	0.94 (0.62, 1.45)	-2 (-20, 10)
Ike (2008)	Marion County, IN	2008-09-14	23.2	0.92 (0.69, 1.22)	-14 (-72, 29)	1.01 (0.74, 1.38)	1 (-21, 17)
Ike (2008)	Wayne County, MI	2008-09-14	23.1	1.00 (0.87, 1.15)	1 (-79, 70)	0.85 (0.62, 1.17)	-33 (-117, 27)
Floyd (1999)	Nassau County, NY	1999-09-16	22.8	1.00 (0.81, 1.22)	-1 (-82, 64)	0.83 (0.63, 1.09)	-15 (-44, 6)

* The total number of Medicare beneficiaries was greater than 50,000 on the day of storm's closest approach to the county.
\# Estimates on the day of storm's closest approach.
& Estimates for the entire storm period.

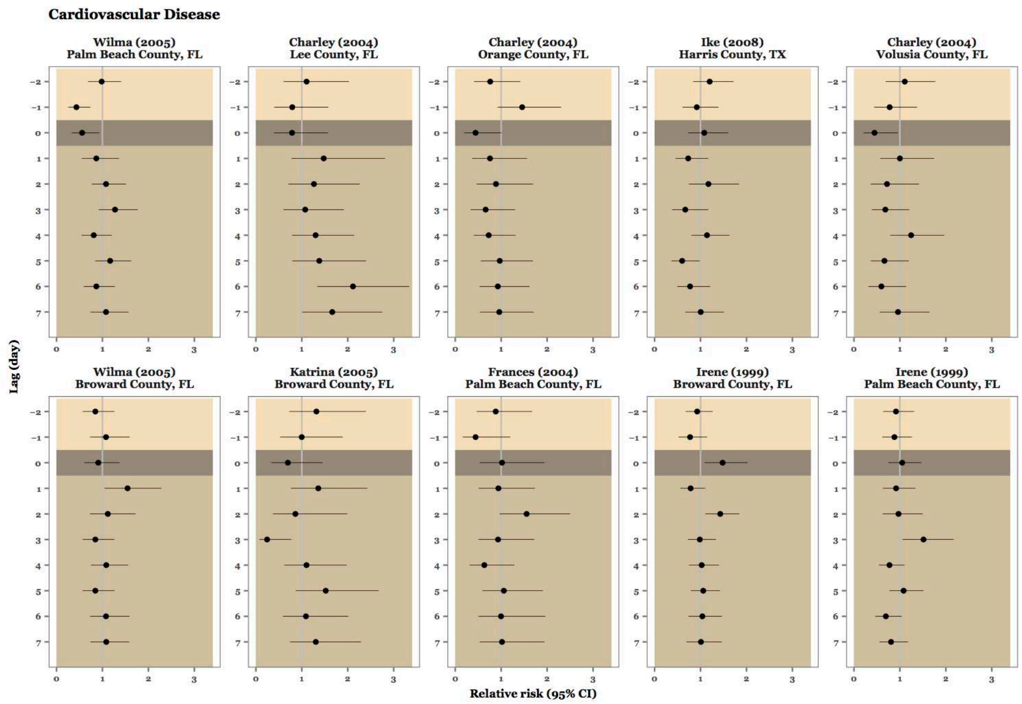

Figure C4 Estimates of distributed relative risks of cardiovascular disease hospitalizations for the ten most severe wind-based tropical cyclones, among **out-of-Florida** counties with total number of Medicare beneficiaries greater than 50,000.

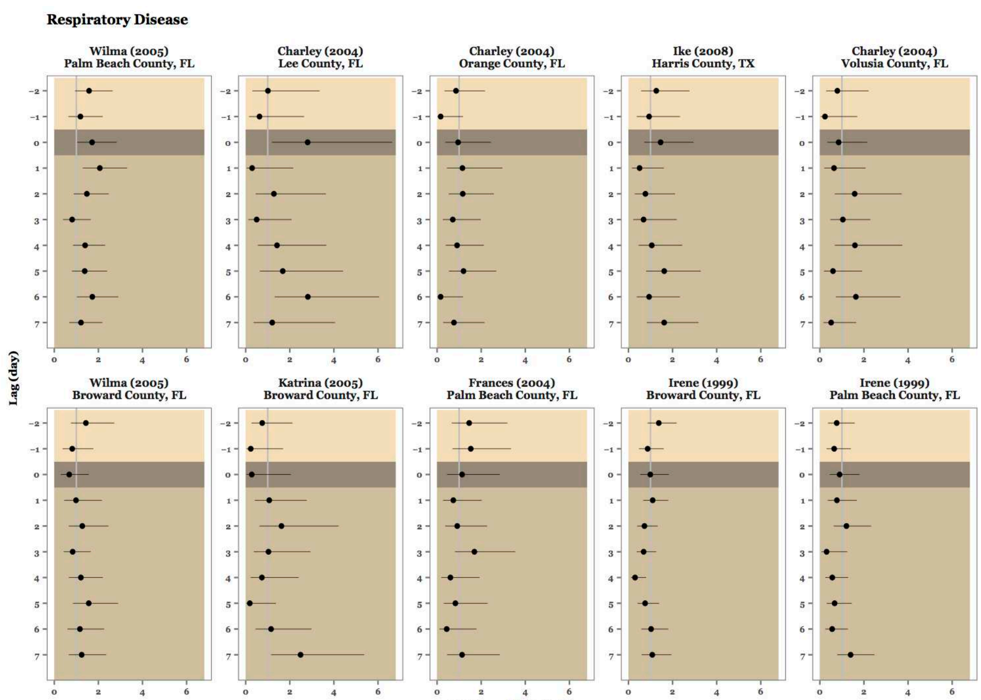

Figure C5 Estimates of distributed relative risks of cardiovascular disease hospitalizations for the ten most severe wind-based tropical cyclones, among **out-of-Florida** counties with total number of Medicare beneficiaries greater than 50,000.

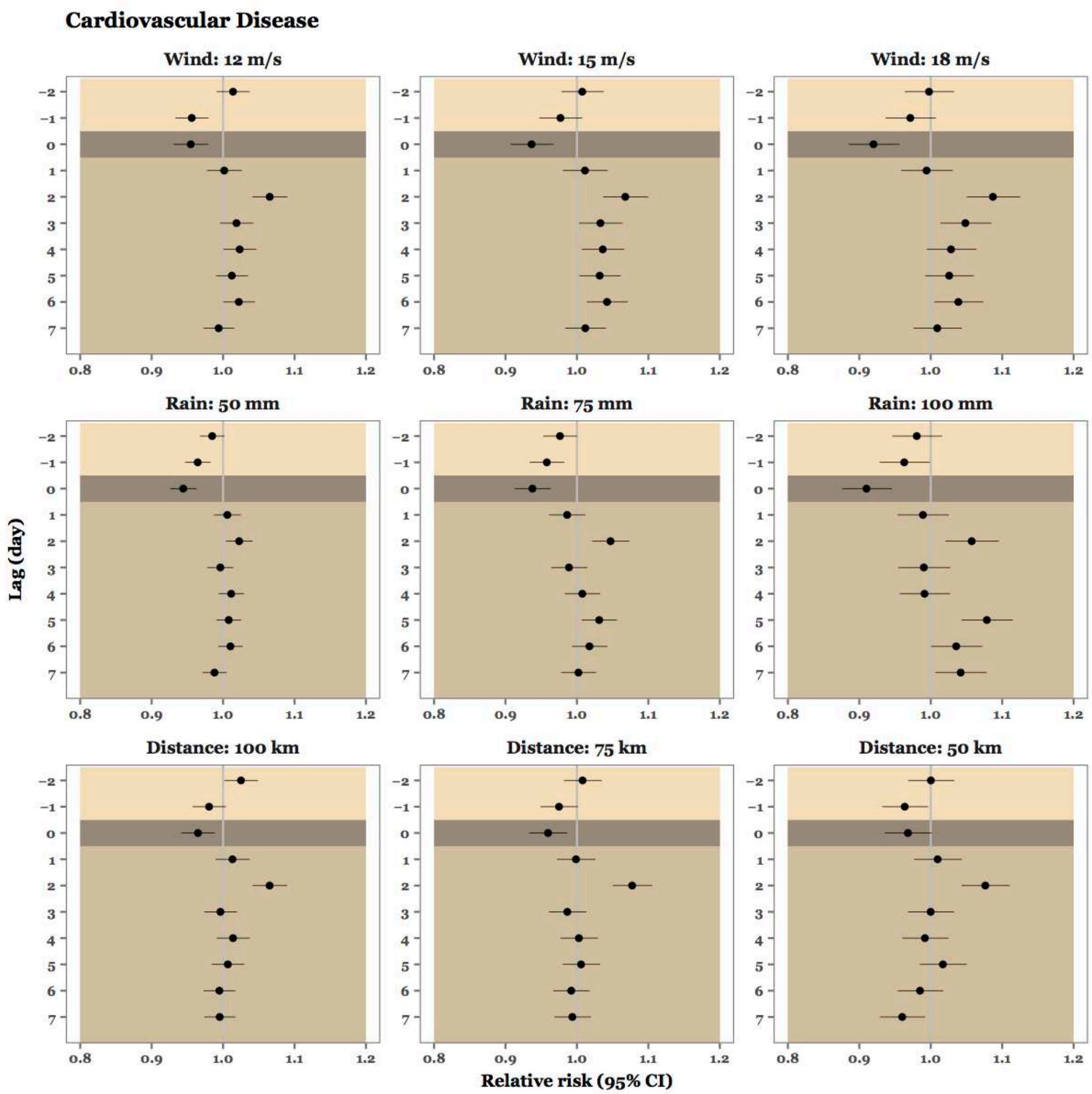

Figure C6 Estimates of distributed relative risks for cardiovascular disease hospitalizations for all tropical cyclones and across all the exposed counties, under the less lenient wind-, rain-, and distance-based exposure metrics.

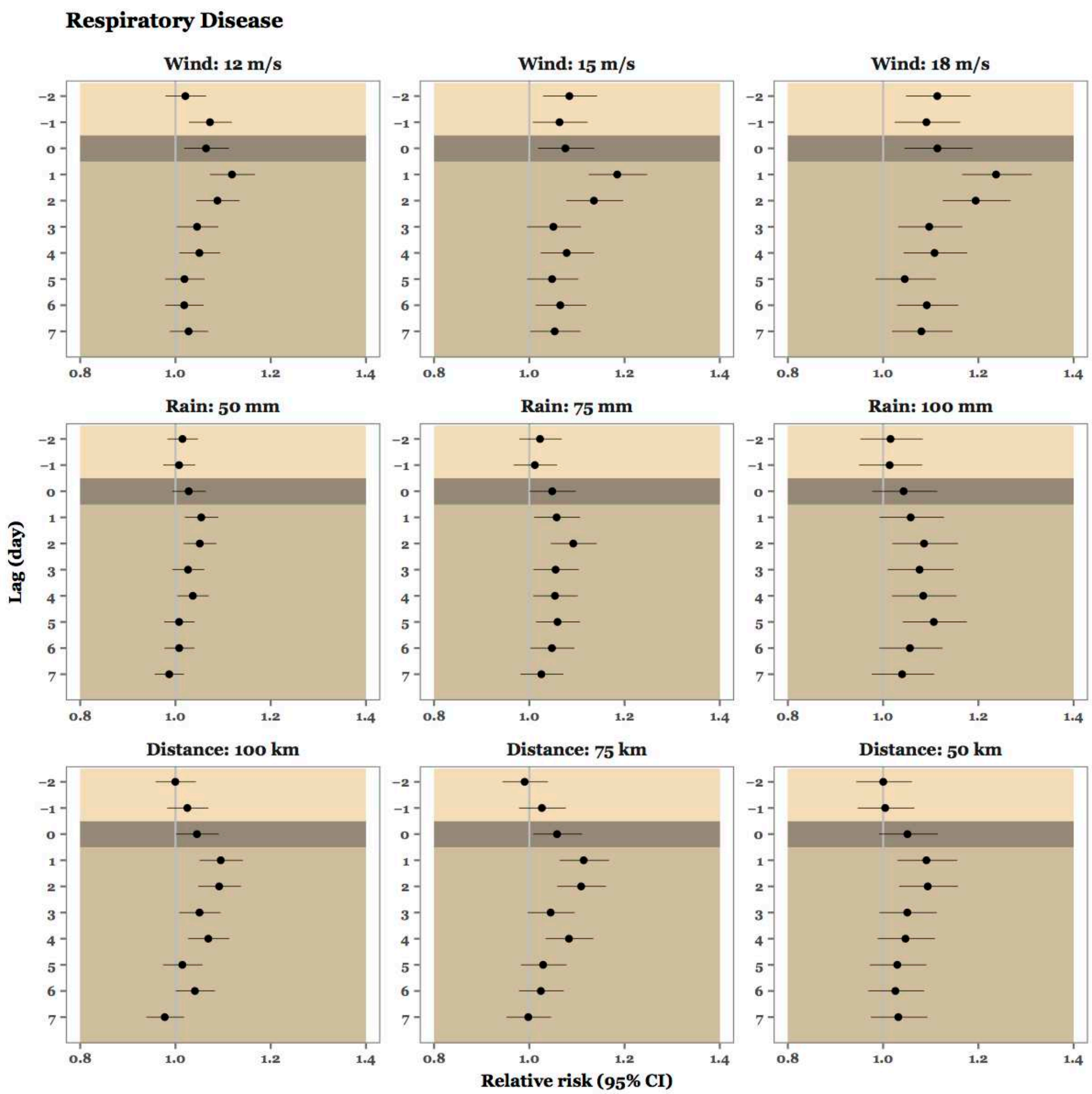

Figure C7 Estimates of distributed relative risks for respiratory disease hospitalizations for all tropical cyclones and across all the exposed counties, under the less lenient wind-, rain-, and distance-based exposure metrics.

Appendix D: Additional analyses of health effects for the most severe wind-based tropical cyclone exposures using time-series and case-crossover

1. Chapter overview

The methodology is still in development for estimating how community-wide health risks during and immediately after a disaster differ from expected rates had the disaster not occurred. One potential approach is to use the study designs common in studying ambient exposures like air pollution and temperature, including time series (1,2) and time-stratified case-crossover study designs (3,4). In this dissertation, we used a matching approach, which compares health outcome rates on disaster-exposed days to those on similar unexposed days in different years. We selected this approach given a few potential concerns about using time series and case-crossover study designs in estimating community-wide impact of natural disaster exposures. First, these two methods may struggle to yield valid estimates if natural disasters have extended impacts on community-wide health risks beyond the modeled period of risk. Further, since tropical cyclones have apparent seasonal pattern, effect estimates based on time-stratified case-crossover might be influenced by the frequency of storm exposure within a given time stratum. To assess whether our primary results are sensitive to modeling choice, we conducted sensitivity analysis in this Chapter using time series and time-stratified case-crossover study designs, analyzing the morbidity and mortality risk of ten most severe wind-based storm exposures, as examined in Chapter 3 and 4.

Methods description. In the time series analysis, we fit a generalized linear model with an overdispered Poisson distribution to the time series data for each community. We used a natural cubic spline function of time with 7 degree of freedom per year in the model to control for seasonal and long-term trends in the health outcome, a natural spline function of temperature with 3 degree of freedom to control for temperature, and a indicator variable to control for day of week. In the case-crossover analysis, we used the time-stratified variant of the case-crossover design, defining the case day as the storm-exposed day and control days as those in the same year, month of year, and day of week as the case day for each stratum of analysis.

2. Estimated relative risks of most severe wind-based storm exposures on mortality

In Chapter 3, we analyzed the lag-specific relative risks (RRs) of the ten most severe wind-based storm exposures on all-cause and cardiovascular mortality, as compared to the matched unexposed days. These results are shown in Figure B2 (all-cause mortality) and B3 (cardiovascular mortality) in Appendix B. Here, we used time series and case-crossover methods to estimate the RRs for these single storm exposures, and then compared these results with our primary results as a sensitivity analysis of our study design choice.

Estimates from time series analysis versus that from primary analysis. The majority of the estimated lag-specific RRs of tropical cyclone exposures for all-cause (Figure D1) and cardiovascular mortality (Figure D2) are consistent with estimates from our primary analysis (Figure B2–B3 in Appendix B), with the exception of Hurricane Katrina. While a RR of 48.29 (95% CI, 38.89–59.97) for all-cause mortality from exposure to Hurricane Katrina in New Orleans was estimated on the day of storm's closest approach (i.e., lag 0) based on our primary matched-analysis approach, we estimated a RR of 135.90 (95% CI, 112.89–163.60) using the time series analysis. The RR of Hurricane Katrina for cardiovascular mortality was also much higher when using time series compared with our primary results (RR: 68.94 *vs.* 19.64).

Further, we investigated if the effect estimates using time series were sensitive to how much flexibility was applied in the spline function of time, which was included in the model to control for the long-term and seasonal trend of mortality rate. When the degree of freedom (d.f.) per year for the spline function of time was set at 3, 6, 9, and 11, the estimated RRs on the day of storm's closest approach for Hurricane Katrina in New Orleans were 109, 98, 94, 135, respectively. Due to the devastating health impacts of Hurricane Katrina in New Orleans, the effect estimates were extremely sensitive to this parameter used in the model, making the time series analysis struggle to estimate an accurate association. However, estimates for other storms were very robust to this certain parameter; for example, the RRs for Hurricane

Andrew in Miami were 1.43, 1.38, 1.39, and 1.41 when using d.f. of 3, 6, 9, and 11. Taken together, time series analysis may struggle to estimate a valid community-wide effect on mortality from exposure to tropical cyclones, in particular when there was extraordinary health impact caused by that storm.

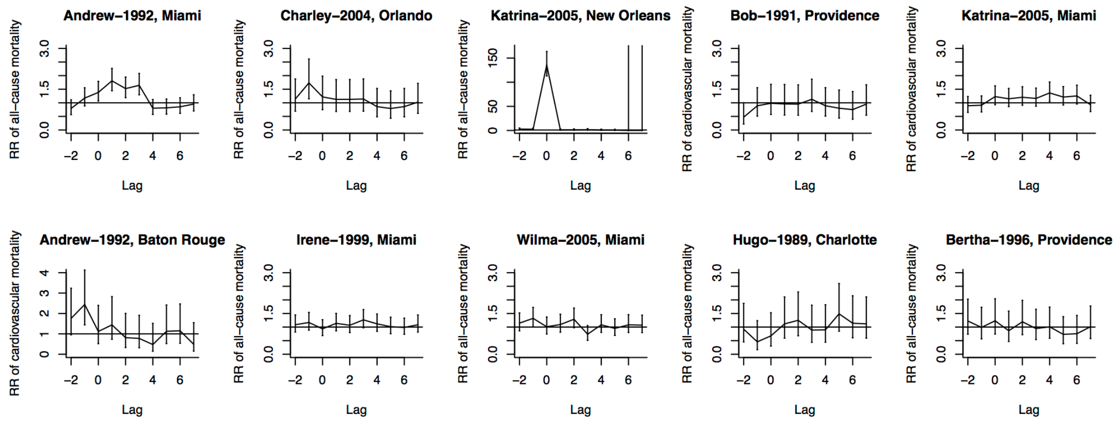

Figure D1 Estimates of lag-specific relative risk of all-cause mortality on days during storm periods, under the most severe wind-based storm exposures among communities with population greater than 400,000. Results were estimated using time series analysis.

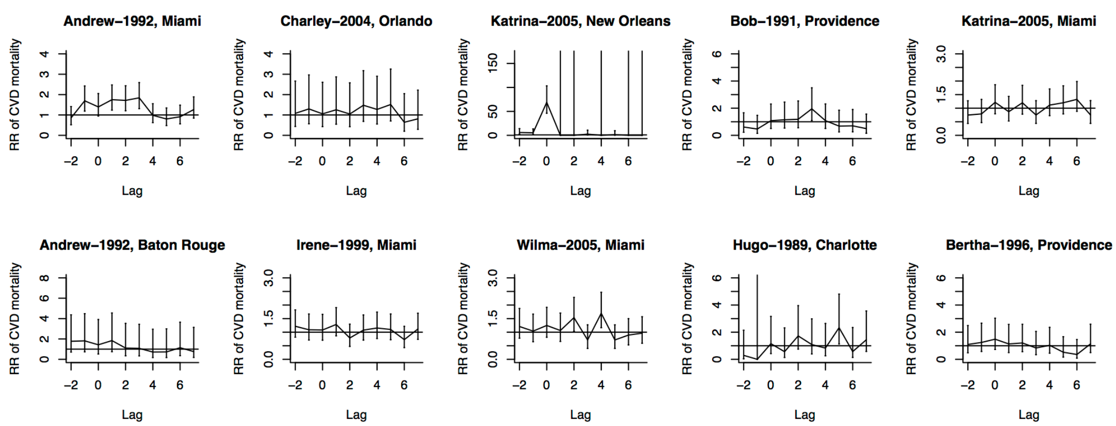

Figure D2 Estimates of lag-specific relative risk of cardiovascular (CVD in the plot) mortality on days during storm periods, under the most severe wind-based storm exposures among communities with population greater than 400,000. Results were estimated using time series analysis.

Estimates from case-crossover analysis versus that from primary analysis. The estimates of lag-specific RRs of tropical cyclones on mortality are generally closer to the null for both all-cause and cardiovascular mortality when using the case-crossover analysis (Figure D3–D4), as compared to our primary results (Figure B2–B3 in Appendix B). For Hurricane Andrew in Miami, the RR for all-cause mortality on the day of storm's closest approach was 1.50 (95% CI, 1.19–2.00) in our primary methods and 1.11 (95% CI, 0.95–1.28) from the case-crossover analysis. The difference in the effect estimates may in part result from the comparison unexposed groups in the two methods. In the case-crossover analysis, the RRs were estimated by comparing the storm days with other days in the same time stratum, which were in the same year, month of year, and day of week as the storm day. Using this time-stratified variant in the case-crossover analysis, the estimated association might be underestimated in two situations: 1) the storm investigated had extended impacts mortality risk on the community, including in some days following the storm that were not identified as "exposed" within the study; or 2) there are different storms approaching the study community within or on the surrounding days of the analyzed time stratum. Both situations are very likely to occur in the context of tropical cyclone, especially during the storm season. By contrast, in our primary analysis, we compared mortality rates on storm-exposed days with the matched non-storm days which were 1) in a different year; 2) within a seven-day window of the storm day's day of year; 3) not in a three-day window of a different storm day for the community; 4) not in the two-week period starting on September 11, 2001. By establishing specific selection criteria for comparison days, we could eliminate potential impacts from the two situations as noted above.

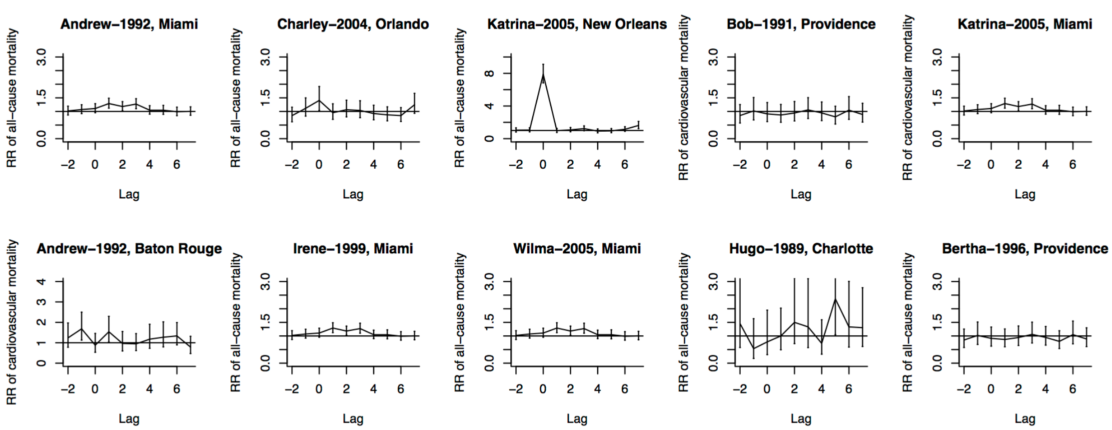

Figure D3 Estimates of lag-specific relative risk of all-cause mortality on days during storm periods, under the most severe wind-based storm exposures among communities with population greater than 400,000. Results were estimated using case-crossover analysis.

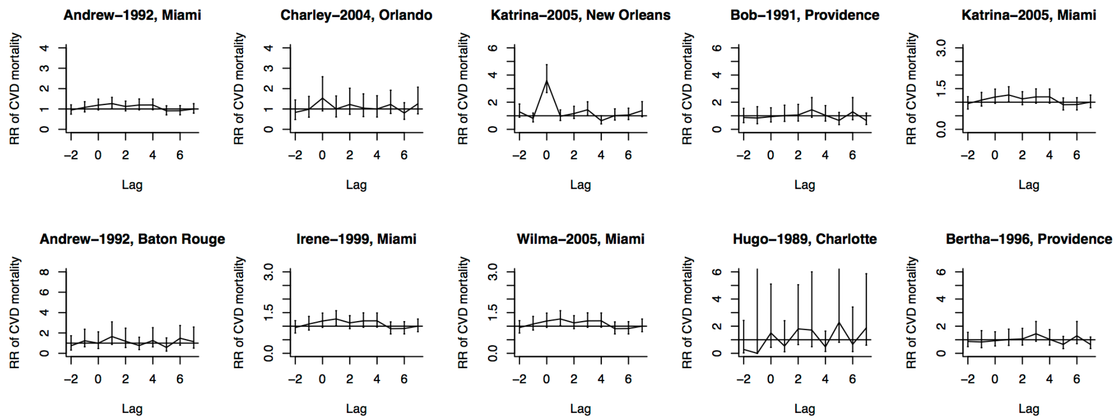

Figure D4 Estimates of lag-specific relative risk of cardiovascular (CVD in the plot) mortality on days during storm periods, under the most severe wind-based storm exposures among communities with population greater than 400,000. Results were estimated using case-crossover analysis.

3. Estimated relative risks of most severe wind-based storm exposures on emergency hospital admissions

In Chapter 4, we analyzed the lag-specific relative risks (RRs) of the ten most severe wind-based storm exposures on emergency hospital admissions due to cardiovascular and respiratory disease, as compared to matched unexposed days. The results were shown in Figure C2 (Cardiovascular disease) and C3 (respiratory disease) in Appendix C. Here, we used time series and case-crossover methods to estimate the RRs for these single storm exposures, and then compared with our primary results.

Estimates from time series analysis versus that from primary analysis. The estimated lag-specific RRs of tropical cyclone exposures for emergency hospital admissions (Figure D5–D6) are mostly consistent with those from our primary analysis (Figure C2–C3 in Appendix C).

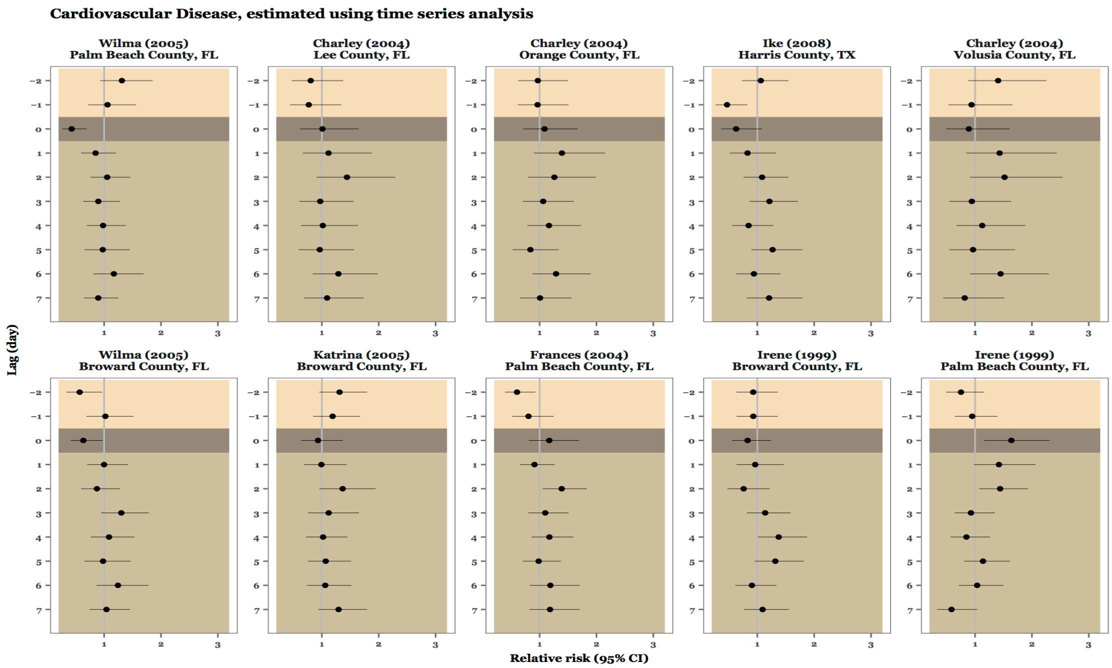

Figure D5 Estimates of lag-specific relative risk of cardiovascular disease hospitalizations on days during storm periods, under the most severe wind-based storm exposures among counties with total number of Medicare beneficiaries greater than 50,000. Results were estimated using time series analysis.

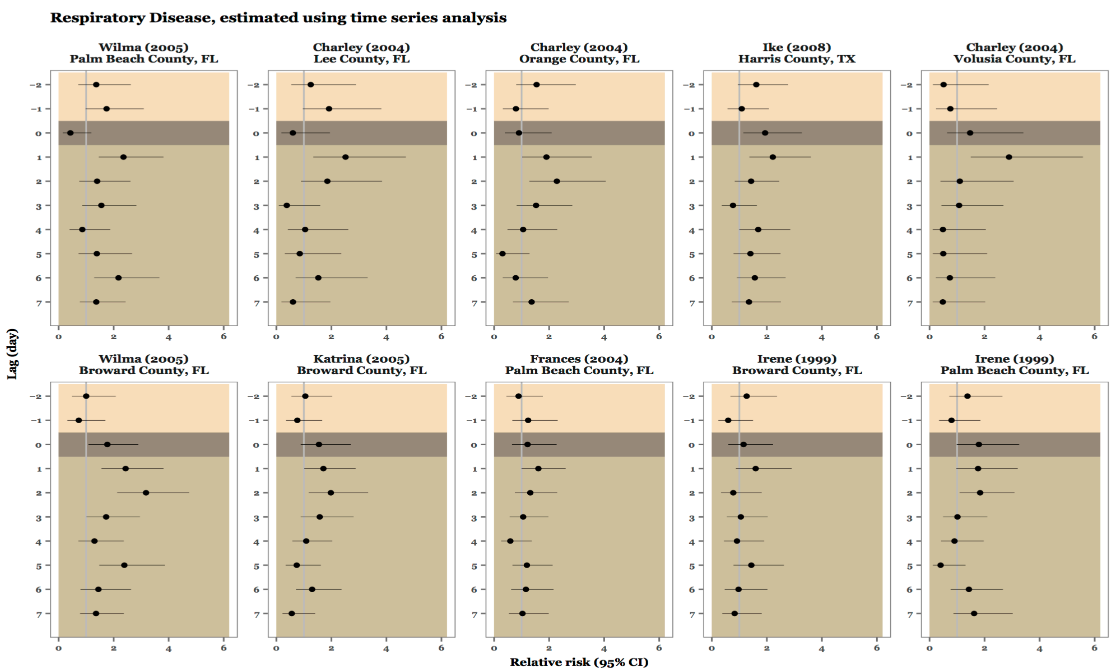

Figure D6 Estimates of lag-specific relative risk of respiratory disease hospitalizations on days during storm periods, under the most severe wind-based storm exposures among counties with total number of Medicare beneficiaries greater than 50,000. Results were estimated using time series analysis.

Estimates from case-crossover analysis versus that from primary analysis. Compared with our primary results, the estimates for the storm-hospitalization association based on a case-crossover analysis are closer to the null (Figure D7–D8), which is in agreement with the comparison for tropical cyclones and mortality associations.

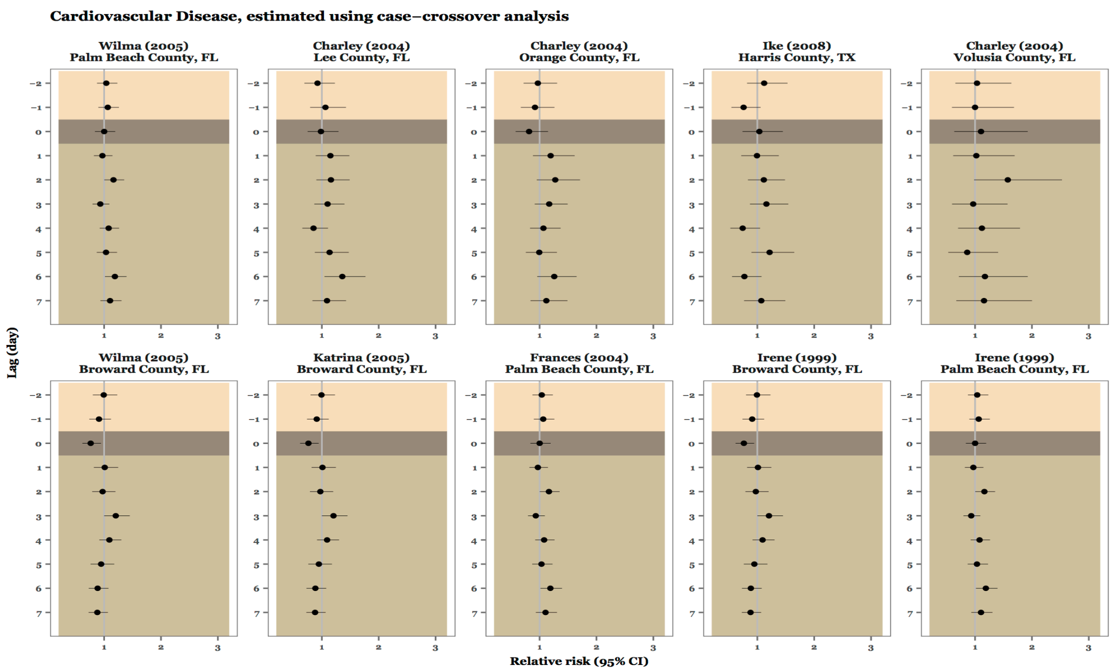

Figure D7 Estimates of lag-specific relative risk of cardiovascular disease hospitalizations on days during storm periods, under the most severe wind-based storm exposures among counties with total number of Medicare beneficiaries greater than 50,000. Results were estimated using case-crossover analysis.

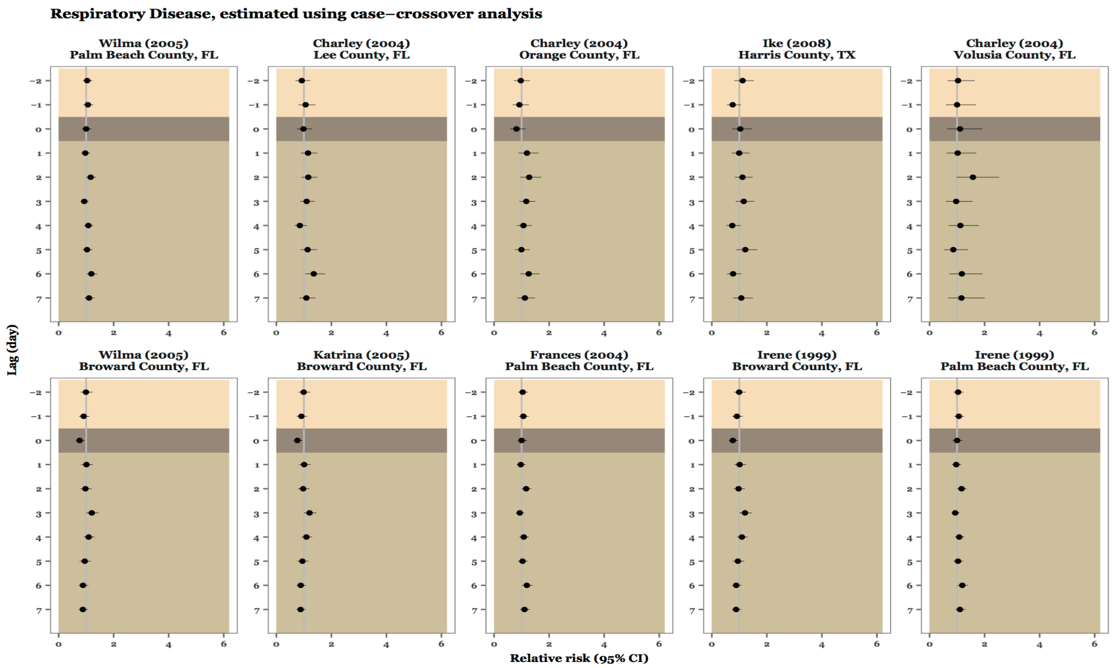

Figure D8 Estimates of lag-specific relative risk of respiratory disease hospitalizations on days during storm periods, under the most severe wind-based storm exposures among counties with total number of Medicare beneficiaries greater than 50,000. Results were estimated using case-crossover analysis.

References

1. Schwartz J, Marcus A. Mortality and air pollution in London: A time series analysis. *American Journal of Epidemiology*. 1990;131(1):185–194.

2. Anderson GB, Bell ML. Heat waves in the United States: Mortality risk during heat waves and effect modification by heat wave characteristics in 43 US communities. *Environmental Health Perspectives*. 2011;119(2):210.

3. Neas LM, Schwartz J, Dockery D. A case-crossover analysis of air pollution and mortality in Philadelphia. *Environmental Health Perspectives*. 1999;107(8):629.

4. Gronlund CJ, Zanobetti A, Schwartz JD, et al. Heat, heat waves, and hospital admissions among the elderly in the United States, 1992–2006. *Environmental Health Perspectives*. 2014;122(11):1187.