Hurricanes and Health

The association between cardiorespiratory Medicare hospitalizations and tropical cyclones

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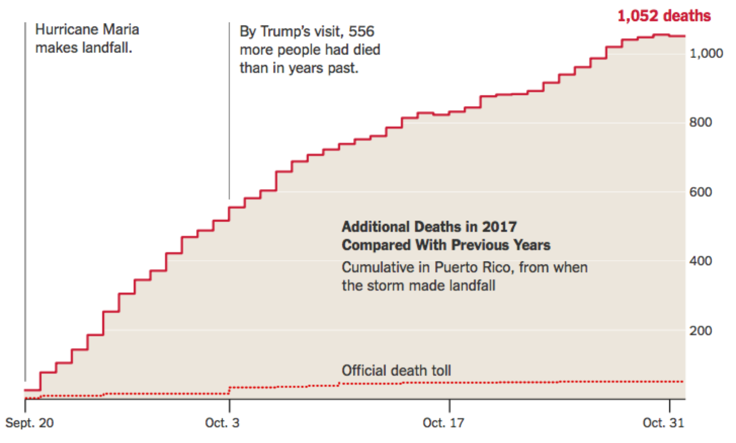
Motivation

Impacts in excess of official death tolls

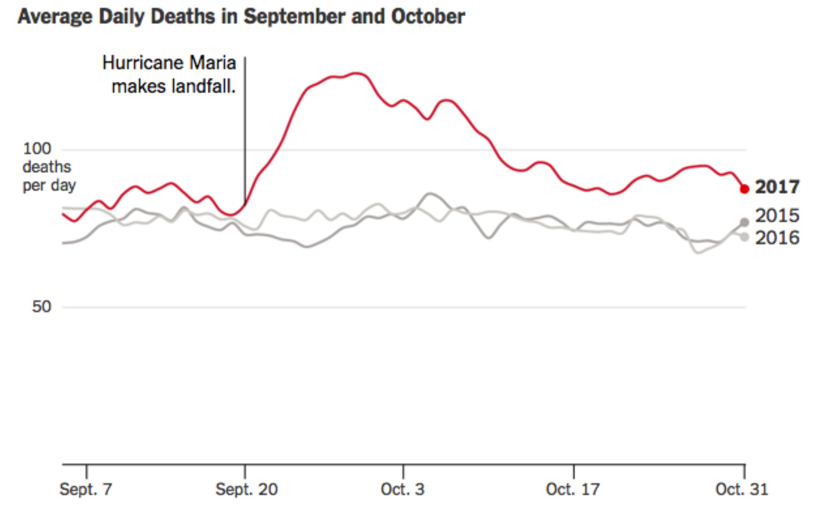
Evidence from Hurricane Maria in Puerto Rico of extensive mortality impacts.



Source: The New York Times

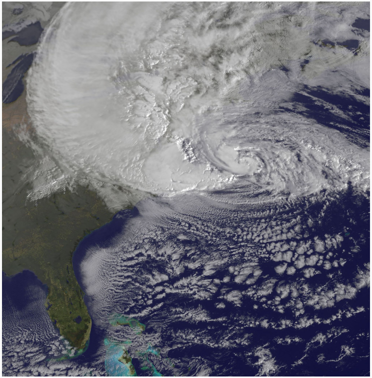
Impacts in excess of official death tolls

Evidence from Hurricane Maria in Puerto Rico.



Source: The New York Times

Health risks associated with Hurricane Sandy (2012)



Source: NOAA / NASA GOES Project

Health risks in storm-affected areas

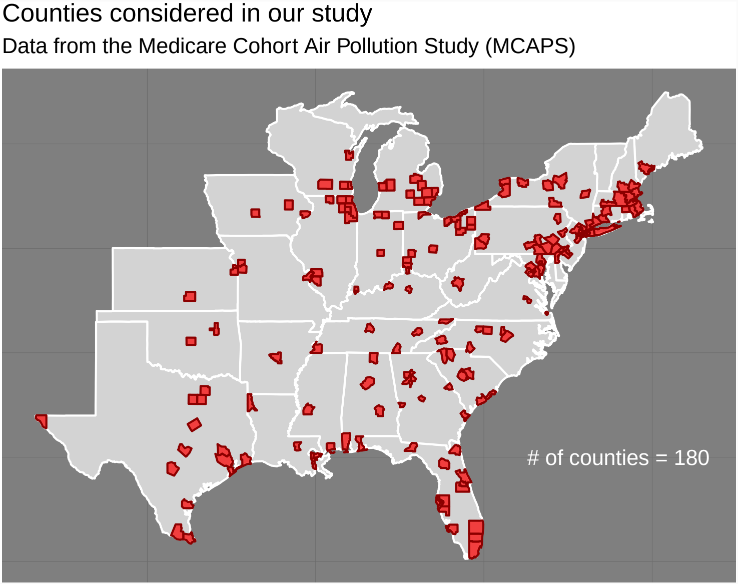
- Change in patterns of emergency department visits (Kim et al. 2016)
- Increased outpatient cases of food and waterborne disease among elderly (Bloom et al. 2016)
- Increased rate of myocardial infarctions (Swerdel et al. 2014)
- Increased hospitalizations for dehydration (Lee et al. 2016)
- Difficulty obtaining medical care, medications, and medical equipment (Davidow et al. 2016)

Study goals

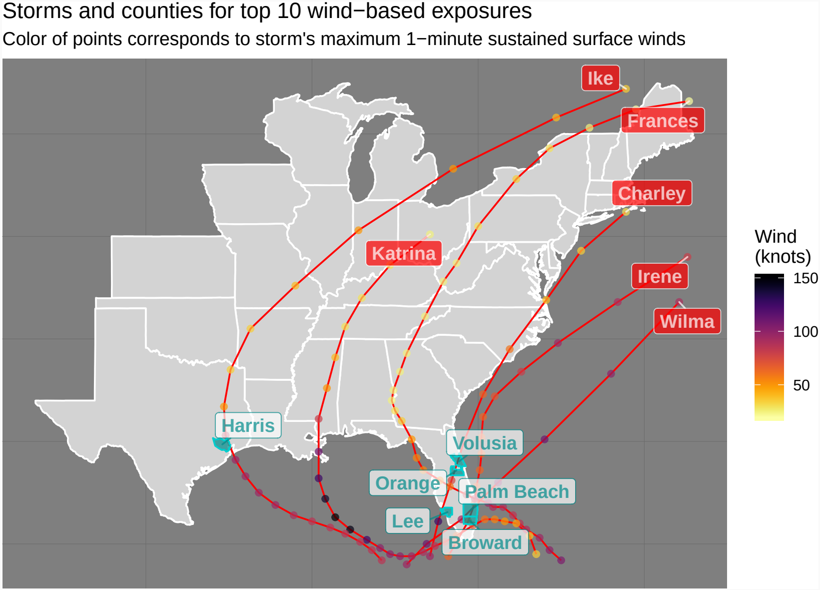
- Investigate how cardiorespiratory Medicare hospitalization risks change during severe tropical cyclone exposures
- Quantify the association between tropical cyclone exposure and cardiorespiratory Medicare hospitalization risks within a large set of exposures and counties
- Explore the temporal pattern in risks in the days surrounding the storm
- Investigate how estimated associations change with changing definitions of tropical cyclone exposure

Methods and Results

All study storms and counties



Top 10 wind-based exposures in our study



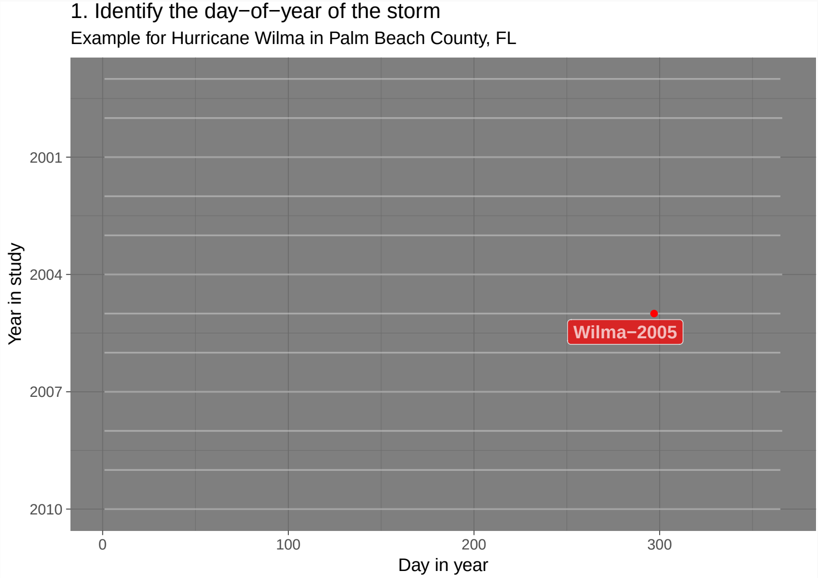
Potential for seasonal confounding

It is important to control for potential seasonal confounding because:

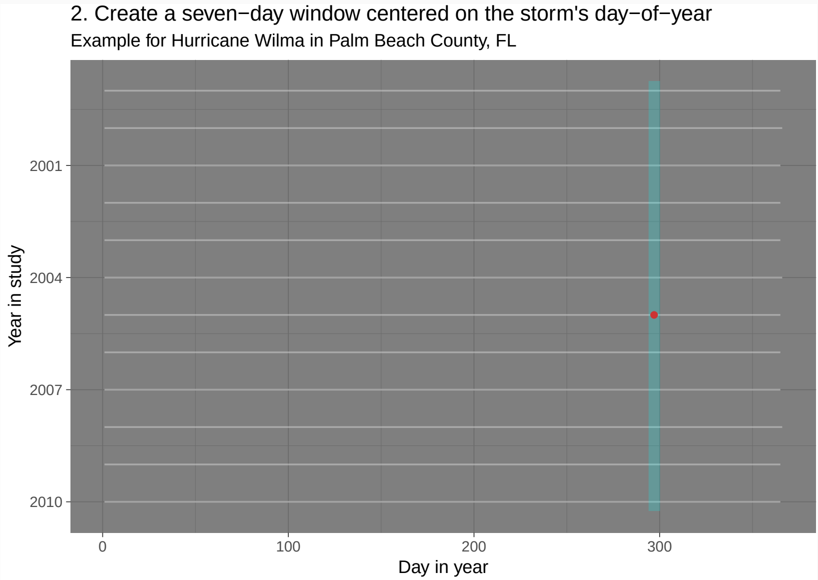
- There are strong seasonal patterns in many **health outcomes**
- There are strong seasonal patterns in **tropical cyclone exposures**

Given this potential for seasonal confounding, we used **a matched analysis** to ensure that the seasonal distribution was similar for exposed and unexposed days, matching across years within a community.

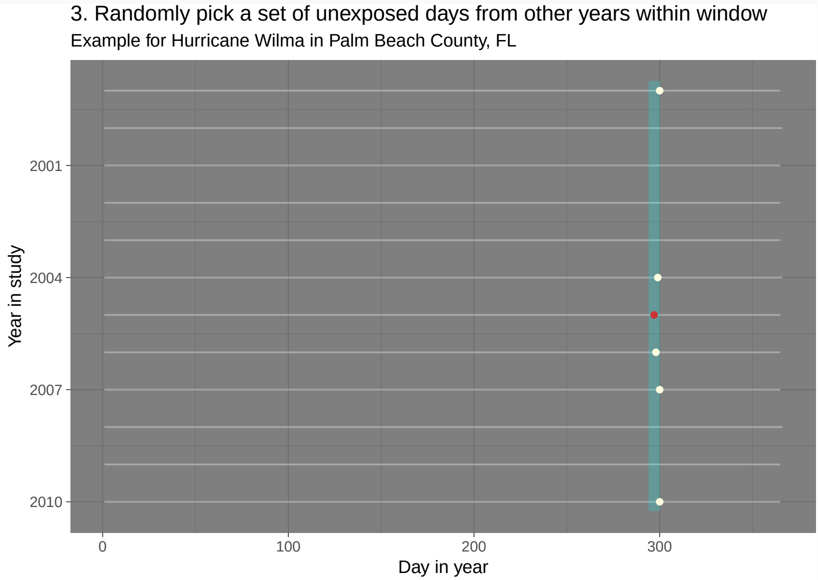
Selecting matched unexposed days



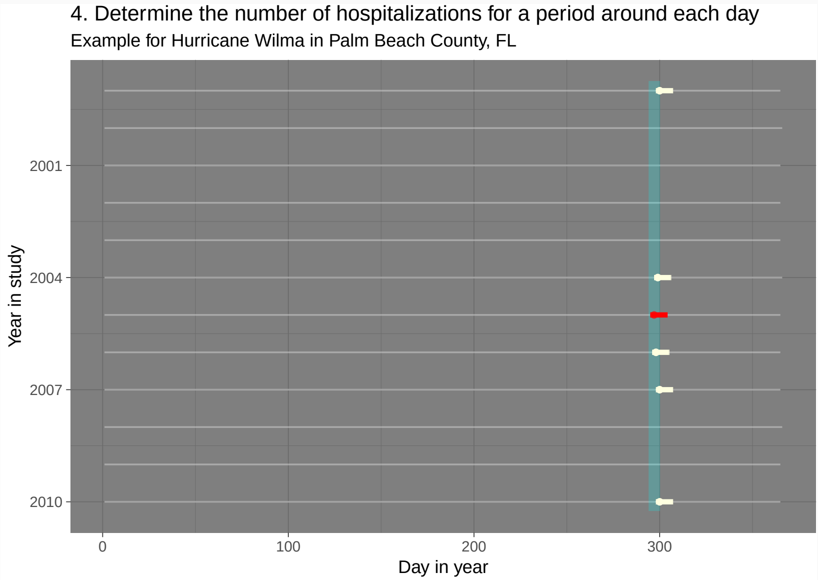
Selecting matched unexposed days



Selecting matched unexposed days



Selecting matched unexposed days



Estimating tropical cyclone-hospitalization associations

We then used this matched data to fit a generalized linear model of hospitalization rates in association with tropical cyclone exposure:

$$log[E(Y_T)] = log(n_T) + \alpha + \beta x_T + \delta Z_T$$

where:

- Y_T is the total count of hospital admissions in the 10-day period T
- n_T is an offset for the number of unhospitalized Medicare beneficiaries in the county in period T
- α is the model intercept
- x_T is an indicator variable for storm exposure, with associated coefficient β
- Z_T is the year of period T, fit as a linear term and with associated coefficient δ

Respiratory hospitalizations

Respiratory hospitalization risks during the top 10 wind-based storm exposures compared to matched unexposed days

Tropical cyclone	County	Wind[a]	Percent increase[b]
Wilma (2005)	Palm Beach County, FL	52	**38 (-3, 95)**
Charley (2004)	Lee County, FL	45	**25 (-10, 73)**
Charley (2004)	Orange County, FL	41	**44 (4, 99)**
Ike (2008)	Harris County, TX	39	**44 (25, 65)**
Charley (2004)	Volusia County, FL	37	**8 (-15, 38)**
Wilma (2005)	Broward County, FL	37	**66 (36, 104)**
Katrina (2005)	Broward County, FL	34	**36 (19, 57)**
Frances (2004)	Palm Beach County, FL	33	**35 (15, 59)**
Irene (1999)	Broward County, FL	33	**10 (-14, 41)**
Irene (1999)	Palm Beach County, FL	33	**40 (-3, 100)**

[a] Modeled maximum sustained surface wind (m/s) at county center

[b] Percent increase in hospitalizations compared to matched unexposed days

Cardiovascular hospitalizations

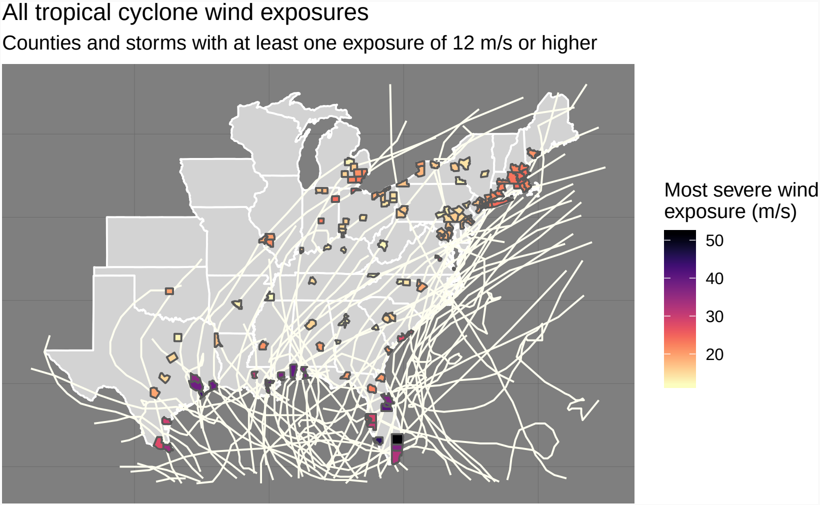
Cardiovascular hospitalization risks during the top 10 wind-based storm exposures compared to matched unexposed days

Tropical cyclone	County	Wind[a]	Percent increase[b]
Wilma (2005)	Palm Beach County, FL	52	-1 (-16, 17)
Charley (2004)	Lee County, FL	45	7 (-6, 21)
Charley (2004)	Orange County, FL	41	20 (2, 41)
Ike (2008)	Harris County, TX	39	-7 (-22, 10)
Charley (2004)	Volusia County, FL	37	23 (-5, 60)
Wilma (2005)	Broward County, FL	37	0 (-15, 18)
Katrina (2005)	Broward County, FL	34	15 (9, 21)
Frances (2004)	Palm Beach County, FL	33	8 (-8, 26)
Irene (1999)	Broward County, FL	33	-11 (-27, 9)
Irene (1999)	Palm Beach County, FL	33	-14 (-30, 7)

[a] Modeled maximum sustained surface wind (m/s) at county center

[b] Percent increase in hospitalizations compared to matched unexposed days

Wind-based exposures in study counties



Estimating tropical cyclone-hospitalization associations

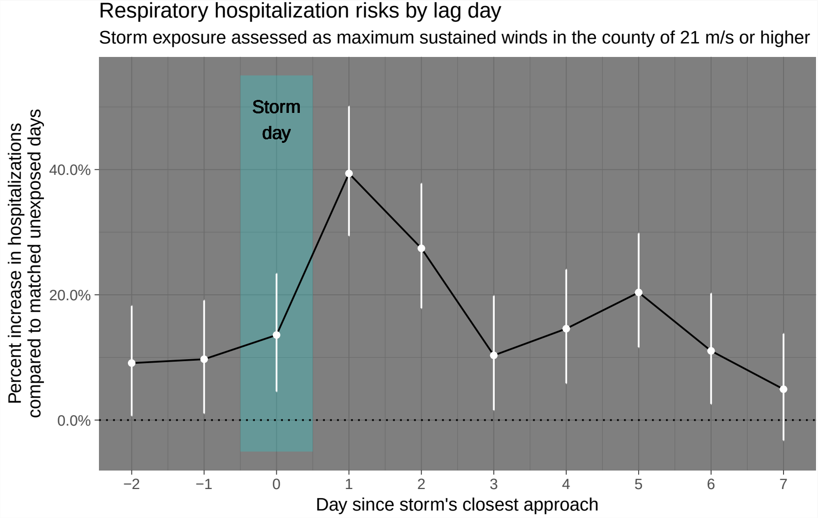
We then used this matched data to fit a generalized linear mixed-effect model of hospitalization rates in association with tropical cyclone exposure:

$$log[E(Y_t^c)] = log(n_t^c) + \alpha + \alpha_c + \sum_{l=-2}^{7} \beta_l x_{t-l}^c + \delta Z_t + \gamma D_t$$

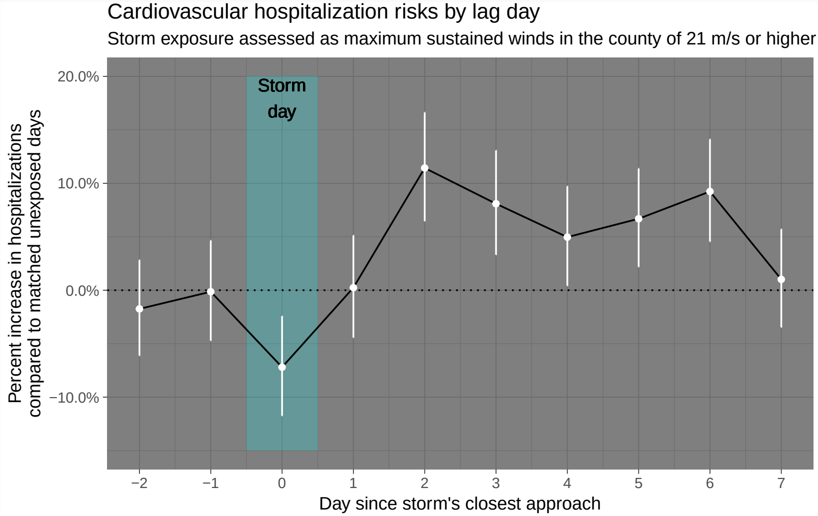
where:

- Y_t is the total count of hospital admissions on day t in community c
- n_T^c is an offset for the number of unhospitalized Medicare beneficiaries in the county on day t in community c
- α is the model intercept
- α_c is a random effect for study county
- x_{t-l} is an indicator variable for storm exposure, with associated lag-specific coefficients β_l
- Z_t is the year of day t, fit as a factor and with associated coefficient δ
- D_t is the day of week of day t, with associated coefficient γ

Hospitalization risks by lag day

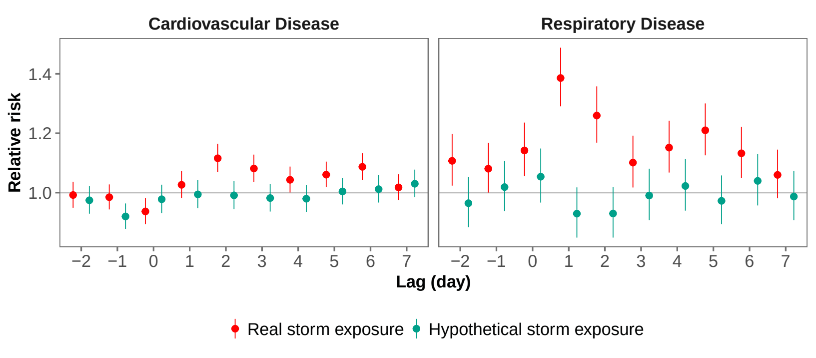


Hospitalization risks by lag day

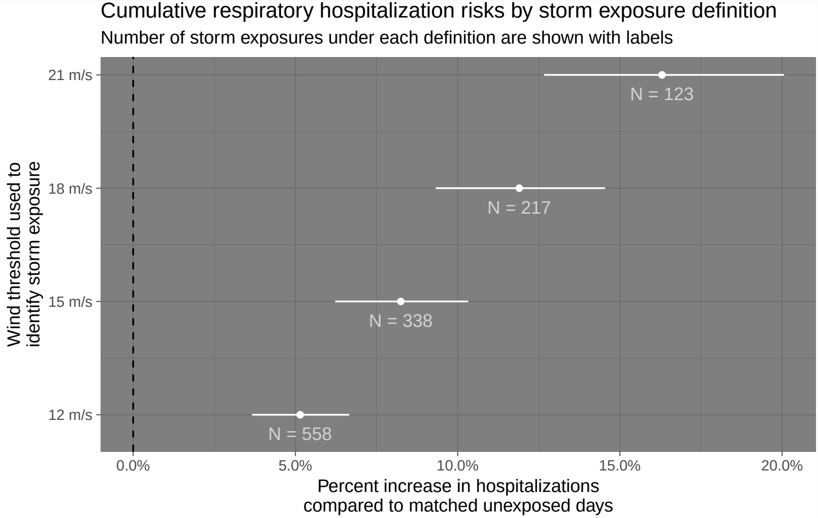


Negative control analysis

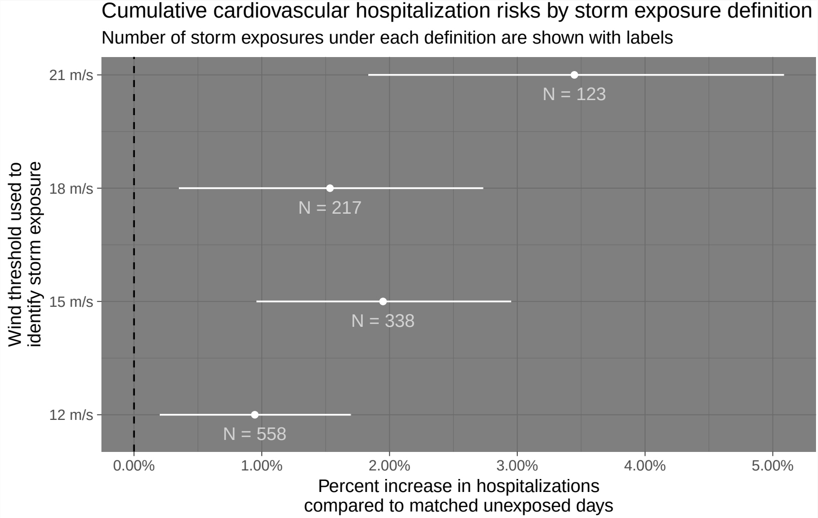
To check for residual confounding by season and year, we conducted a negative control analysis, where we tested our methods using as a negative control the day **two weeks before** each real storm day.



Cumulative risks by storm exposure threshold

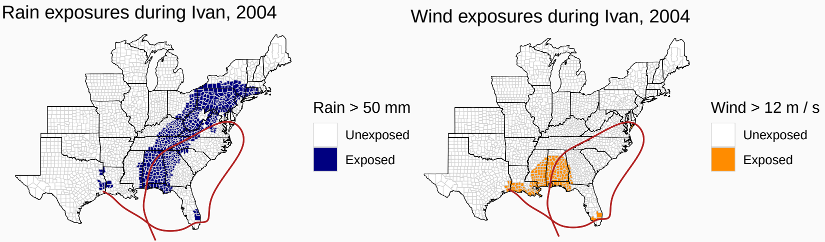


Cumulative risks by storm exposure threshold



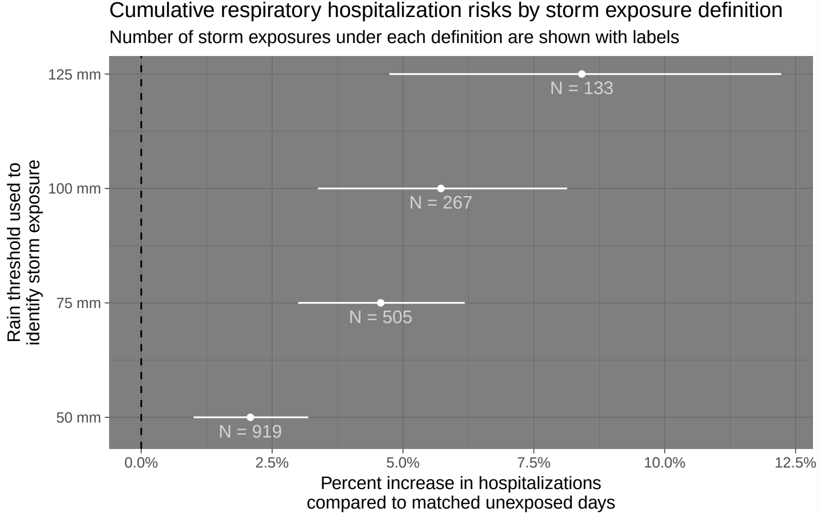
Differences in exposures by hazard

The counties assessed as "exposed" to tropical cyclones can differ substantially based on the hazard metrics considered in assessing exposure.

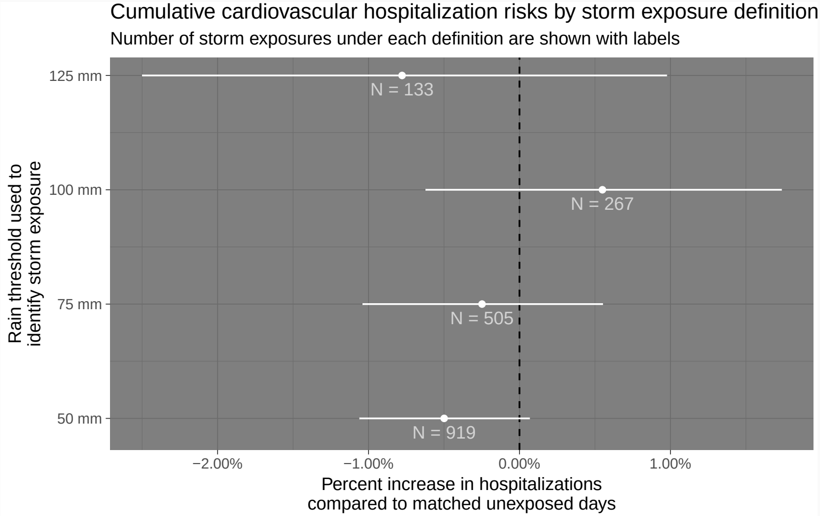


Exposures for Hurricane Ivan based on rain measurements (left) and modeled maximum sustained winds (right).

Cumulative risks under rain-based exposure



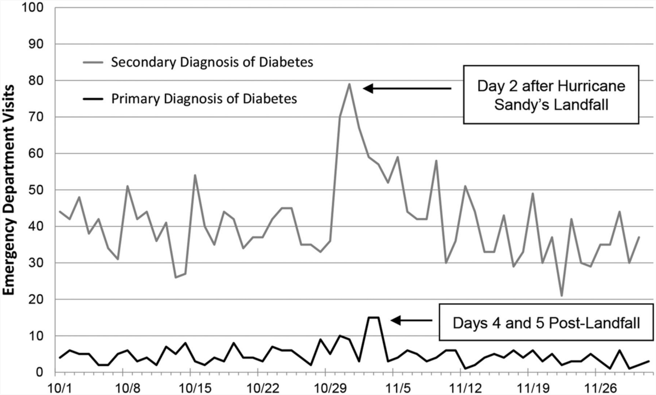
Cumulative risks under rain-based exposure



Discussion

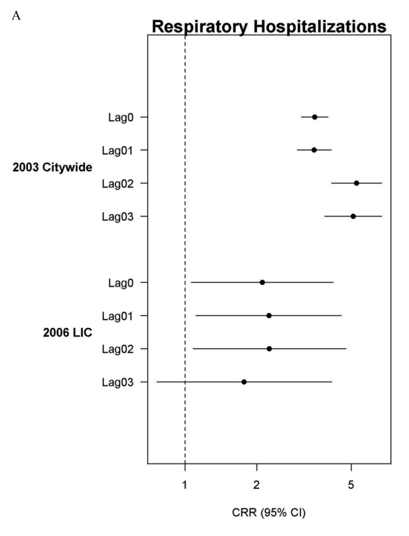
Delayed association with morbidity outcomes

Example of another study that found the largest association between tropical cyclone exposure and morbidity outcomes (emergency department visits among patients with diabetes)



Source: Lee et al. 2016, BMJ Open Diabetes Research and Care.

Potential role of power outages



Risks of respiratory hospitalizations during major New York power outages.

Source: Dominianni et al. 2018, Environmental Health Perspectives.


National Oceanic and Atmospheric Administration
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Study: Climate warming to boost major hurricanes in active Atlantic seasons

Research | hurricanes measuring and modeling climate research

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Based on recent research, climate change is likely to increase the number of major hurricanes in active hurricane seasons

Understanding variation across storms in health effects

Tropical Storm Allison (2001) caused extensive flooding in Houston, TX

Source: National Oceanic and Atmospheric Administration

Climate attribution studies

LETTER

Quantitative attribution of climate effects on Hurricane Harvey's extreme rainfall in Texas

S-Y Simon Wang[1,2], Lin Zhao[3], Jin-Ho Yoon[4,6], Phil Klotzbach[5] and Robert R Gillies[1,2]

Increased threat of tropical cyclones and coastal flooding to New York City during the anthropogenic era

Andra J. Reed[a,1], Michael E. Mann[a,b], Kerry A. Emanuel[c], Ning Lin[d], Benjamin P. Horton[e,f], Andrew C. Kemp[g], and Jeffrey P. Donnelly[h]

HURRICANE SANDY BEFORE 1900 AND AFTER 2100

BY GARY M. LACKMANN

Climate attribution studies

Past, present, and future **intensities** for Hurricane Sandy from an attribution study

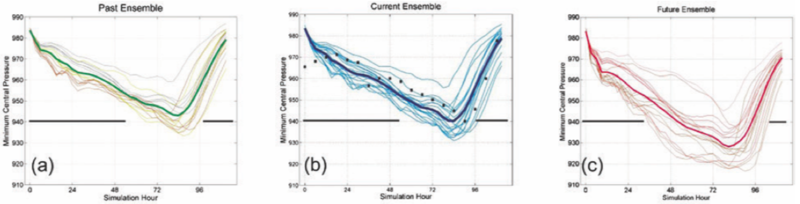


Fig. 7. Time series showing ensemble intensity plots for (a) past, (b) current, and (c) future simulations. Enhanced horizontal line corresponds to landfall intensity of 940 hPa.

Source: Lackmann 2015, BAMS

Climate attribution studies

Past, present, and future **paths** for Hurricane Sandy from an attribution study

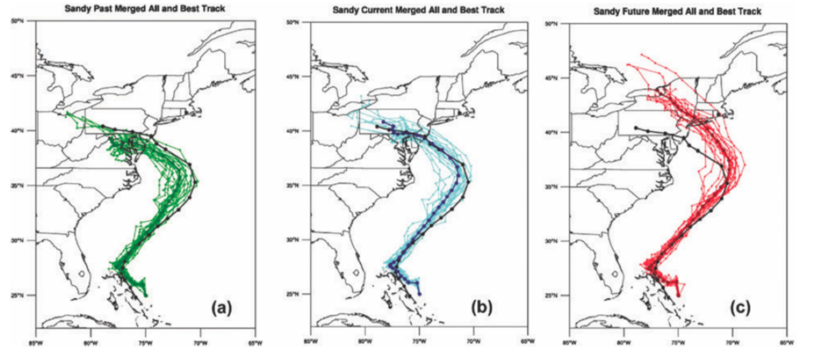


FIG. 5. Track ensembles for (a) past, (b) current, and (c) future paths of Hurricane Sandy, derived from 6-day WRF simulations initialized 0000 UTC 26 Oct. The black line represents the National Hurricane Center best track; lighter colored lines represent ensemble members, and darker colored lines represent ensemble means for past (green), current (blue), and future (red).

Source: Lackmann 2015, BAMS

Other related research in our lab

We have a number of related research projects ongoing in our lab:

- Estimating associations between tropical cyclone exposures and human mortality risks (all-cause, cardiovascular, respiratory, accidental)
- Exploring how the associations between tropical cyclone exposure and health outcomes change across definitions of tropical cyclone exposure
- Enabling access to county-level tropical cyclone exposure data for multiple storm hazards (wind, rain, floods, tornadoes)
- Developing methods for epidemiological research on climate-related disasters
- Quantifying health-related risks for other climate-related disasters, especially extreme temperatures and heat waves

‘hurricaneexposure‘ package

Create county-level exposure time series for tropical storms in U.S. counties. Exposure can be determined based on several hazards (e.g., distance, wind, rain), with user-specified thresholds. On CRAN.

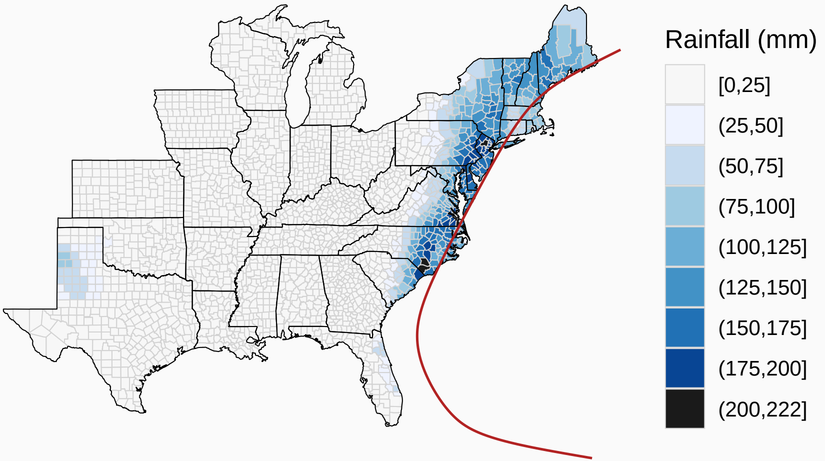
```
county_rain(counties = c("22071", "51700"), rain_limit = 100,
            start_year = 1995, end_year = 2005, dist_limit = 100,
            days_included = c(-1, 0, 1))
```

```
##       storm_id  fips closest_date storm_dist tot_precip
## 1    Bill-2003 22071   2003-06-30   38.78412      141.1
## 2 Charley-2004 51700   2004-08-14   43.01152      136.2
## 3   Cindy-2005 22071   2005-07-06   32.21758      113.2
## 4   Floyd-1999 51700   1999-09-16   46.50729      207.5
```

hurricaneexposure package

The `hurricaneexposure` package can also be used to map exposures for specific storms:

```
map_counties(storm = "Floyd-1999", metric = "rainfall")
```



Questions?

"Remember that hurricane a thousand miles away? That was me!"

Source: The New Yorker