SYSTEMS ENGINEERING RESEARCH CENTER

SERC DOCTORAL STUDENT FORUM 2024 | NOVEMBER 13, 2024

Examination of Community Responses to Hurricane Evacuation Orders Using High-Fidelity Mobility Data

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CASS RESEARCH LAB

Introduction and Motivation

Existing Research and Gaps

Research Objectives

Research Tasks

Conclusion and Future Work

Introduction and Motivation

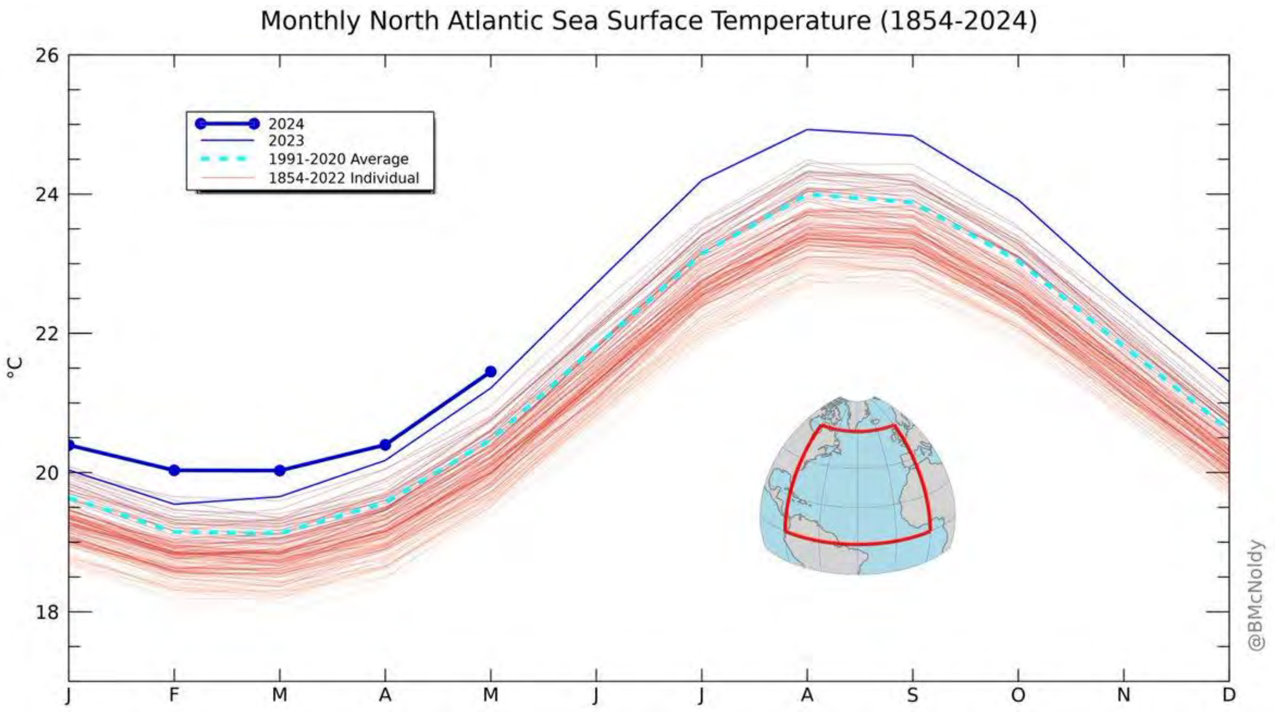


Image sources: https://twitter.com/BMcNoldy/status/1809205990837178580

Introduction and Motivation

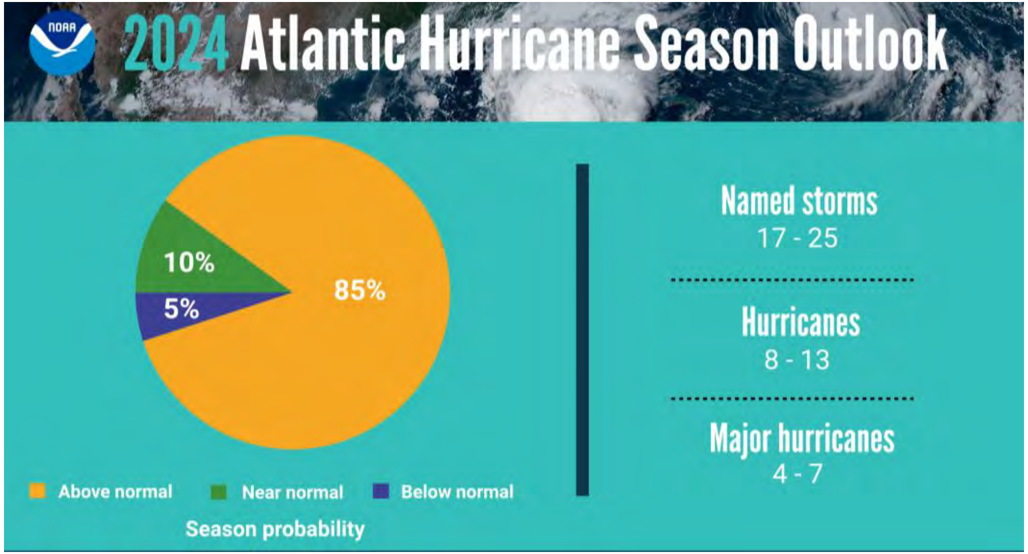
National Oceanic and Atmospheric Administration
U.S. Department of Commerce

Search NOAA sites

Home / News & Features

NOAA predicts above-normal 2024 Atlantic hurricane season

La Nina and warmer-than-average ocean temperatures are major drivers of tropical activity



Category 5 Hurricane Beryl makes explosive start to 2024 Atlantic season

ABC News - Breaking News, Latest News and Videos
https://abcnews.go.com › live-updates › hurricane-helene

Hurricane Helene updates: Death toll surpasses 230 as ...

More than 230 people have been killed from Hurricane Helene, which unleashed devastation across Florida, Georgia, South Carolina, North Carolina, ...

USA Today
https://www.usatoday.com › news › weather › 2024/10/15

Hurricane death toll tops 300 lives, with month left in season

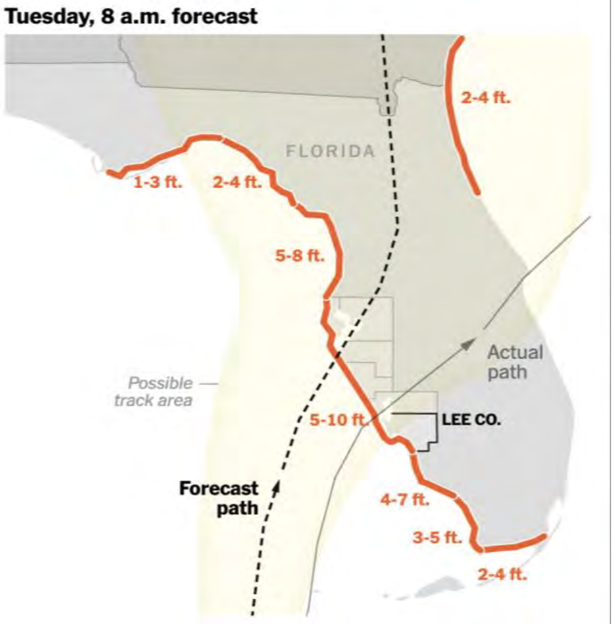
Oct 15, 2024 — By mid-October, **more than 300 deaths** have been directly caused by hurricanes during the Atlantic hurricane season, which ends on Nov. 30.

Image sources: NOAA, Weather Channel

Introduction and Motivation

Started forming on 23rd September 2022

Trajectory on 26th September 2022



Trajectory on 27th September 2022

Image sources: NYTimes, NOAA

Introduction and Motivation

At least 100 dead from Hurricane Ian as Florida's top emergency official defends Lee County over delayed evacuations

Oct. 3, 2022, 12:10 PM EDT / Updated Oct. 3, 2022, 7:25 PM EDT

NATION

45 people died in Lee County, where Ian made landfall. Did officials do enough?

Jane Musgrave Fort Myers News-Press

Published 11:26 a.m. ET Oct. 4, 2022 | Updated 3:33 p.m. ET Oct. 4, 2022

Weather Updates ›

Facing a Dire Storm Forecast in Florida, Officials Delayed Evacuation

The New York Times

WEATHER

Florida officials face questions over the late evacuation order in Lee County

October 3, 2022 · 5:00 AM ET

Florida governor defends the timing of Lee County officials' evacuation ahead of Hurricane Ian

By Andy Rose, Paradise Afshar and Steve Contorno, CNN

Updated 2:30 PM EDT, Sun October 2, 2022

Sources: NYTimes, CNN, NPR, Nation, NBC

Introduction and Motivation

Would the outcome have been different if the evacuation orders had been sent earlier?

How is evacuation behavior motivated by evacuation orders?

What are the influencing factors behind effective evacuations?

Understanding socio-economic disparities for equitable evacuations.

Introduction and Motivation

Existing Research and Gaps

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Evolution of Hurricane Evacuation Decision-Making Research

Historic Attempts of Evacuation Understanding

Post-event surveys and interviews *[Baker, 1991, Thompson et al., 2017]*

Social vulnerabilities (such as income, ethnicity, gender, and race) *[Peacock et al., 2012, Murray-Tuite and Wolshon, 2013]*, Consequences (such as warning and risk perception) *[Dash and Gladwin, 2007, Riad et al., 1999]*, Social influences *[Sadri et al., 2017, Ersing et al., 2020]*, Evacuation orders *[Fischer et al., 1995, Meyer et al., 2018]*

Stated preference surveys and interviews *[Whitehead, 2005, Thompson et al., 2017, Collins 2018]*

Limited generalizability and hypothetical biases
[Hong et al., 2020, Younes et al., 201]

Contemporary Research

- **Geo-tagged social media** *[Kumar and Ukkusuri, 2018, Roy and Hasan, 2021, Martín et al., 2017, Martín et al., 2020]*

Eliminated population bias, suffers from population representativeness
[Martín et al., 2017]

- **High-fidelity mobility data** *[Wang et al., 2020]*
  - Population displacement *[Wang and Taylor, 2014, Wang and Taylor, 2016]*
  - Evacuation patterns and planning improvement *[Yabe et al., 2019a, Yin et al., 2020, Chang and Liao, 2015]*

Ability to capture higher spatio-temporal granularity.

Key Gaps

The **role of evacuation orders** and **the causal interplay** between evacuation orders and decisions remained understudied.

Existing studies often **cover broad areas**, missing targeted, evidence-based insights —a limited **exploration of high-fidelity mobility data.**

Event-based studies with **inconsistent study designs** limit the ability to derive broader, generalizable conclusions.

Introduction and Motivation

Literature Review

Research Objectives

Research Tasks

Conclusion and Future Work

Research Objectives

01
Developing a Hurricane Evacuation Order Data Repository

02
Evaluating the Effectiveness of Hurricane Evacuation Orders

03
Analyzing Evacuation Behavior in Communities During Hurricanes

04
Cross-Hurricane Generalization of Racial and Income Disparities in Evacuation Behavior

Introduction and Motivation

Literature Review

Research Objectives

Research Tasks

- *Task 1: Evacuation Order Database*
- Task 2: Evacuation Order Effectiveness
- Task 3: Communities Evacuation Behavior
- Task 4: Cross-Hurricane Disparity

Conclusion and Future Work

Task 1

Research Objective

Comprehensive Evacuation Order Database Creation

Collate evacuation orders issued by government officials during hurricane events.

Order Type

Can be categorized as either mandatory or voluntary, or the state of emergency.

Announcement Time

Represents the moment when authorities first announce the evacuation order.

Effective Time

Indicates when the evacuation order is officially activated and in effect.

Spatial Element

Defines the specific high-risk areas targeted for evacuation

Task 1

Challenges

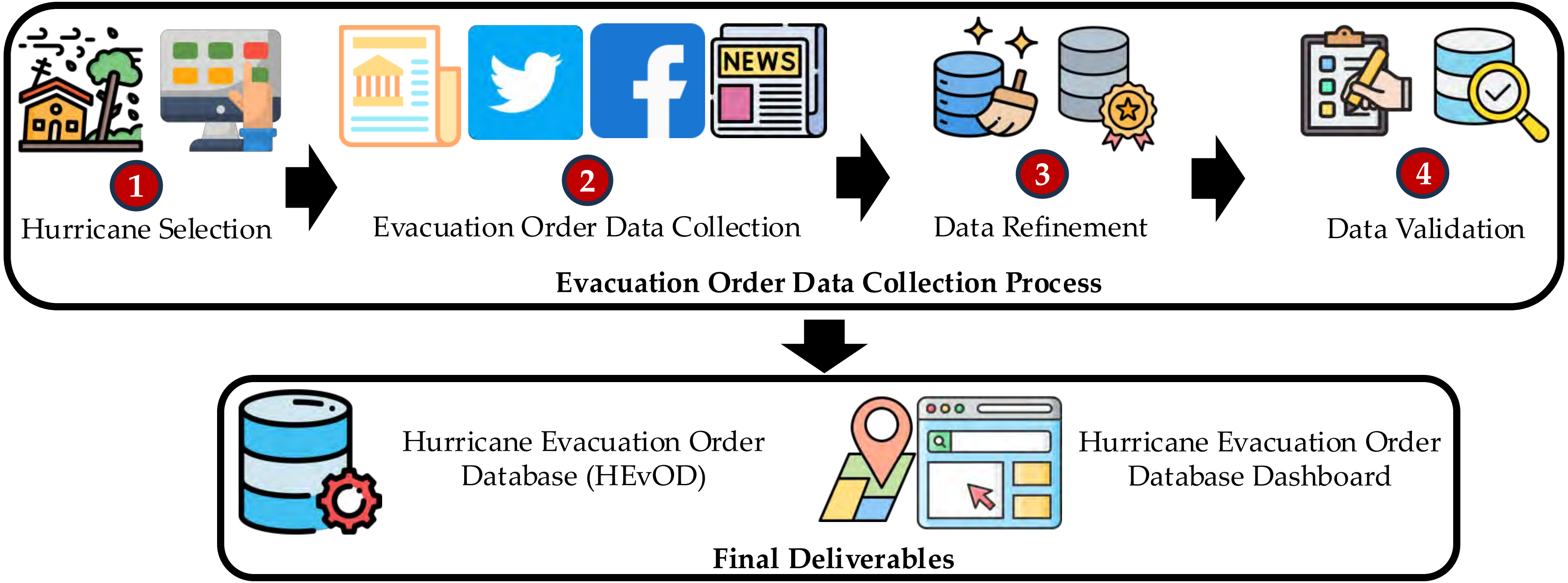
Evacuation laws and policies

Evacuation orders communication style

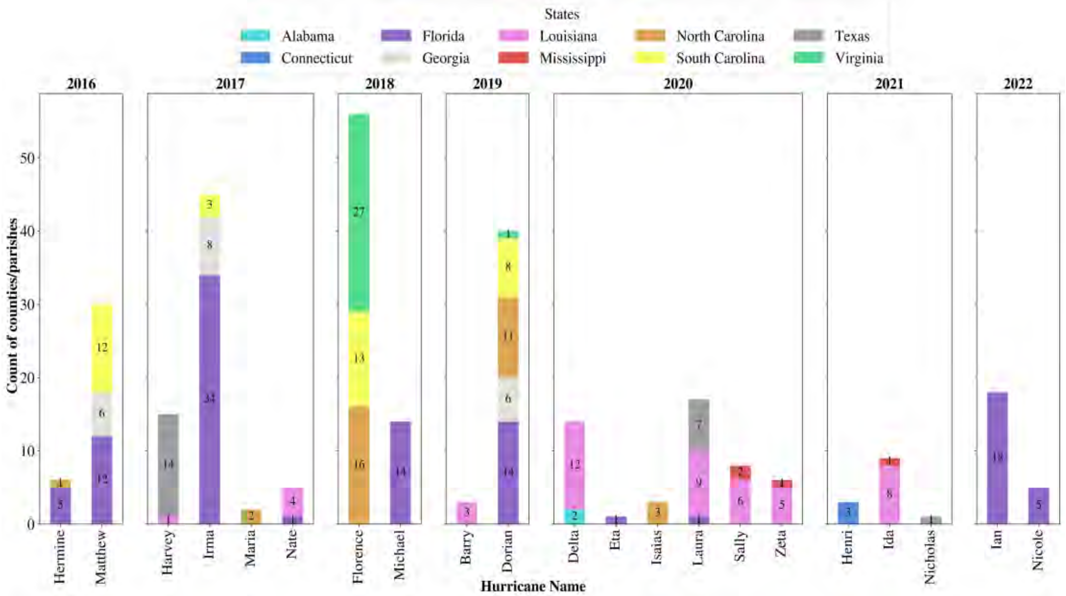
Platforms for spreading evacuation orders

Evacuation order archival

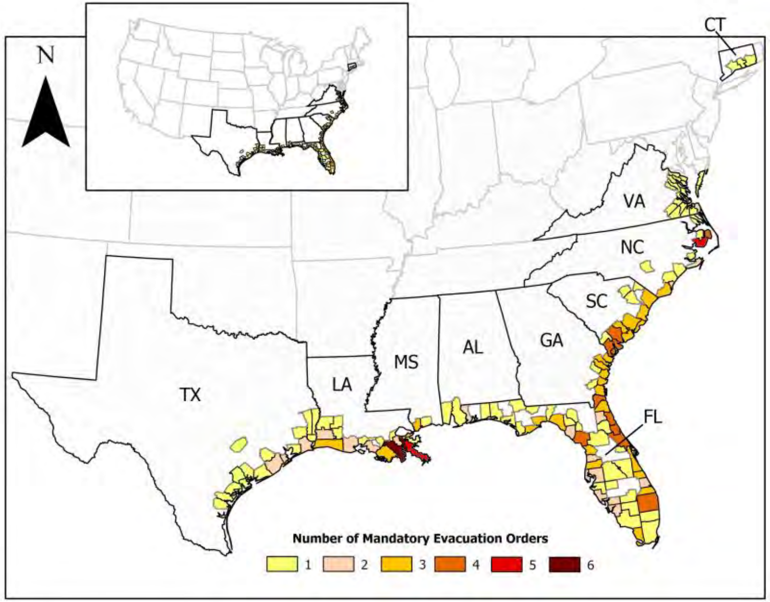
Methodology



HEvOD Data Summary



Number of counties that issued mandatory evacuation orders



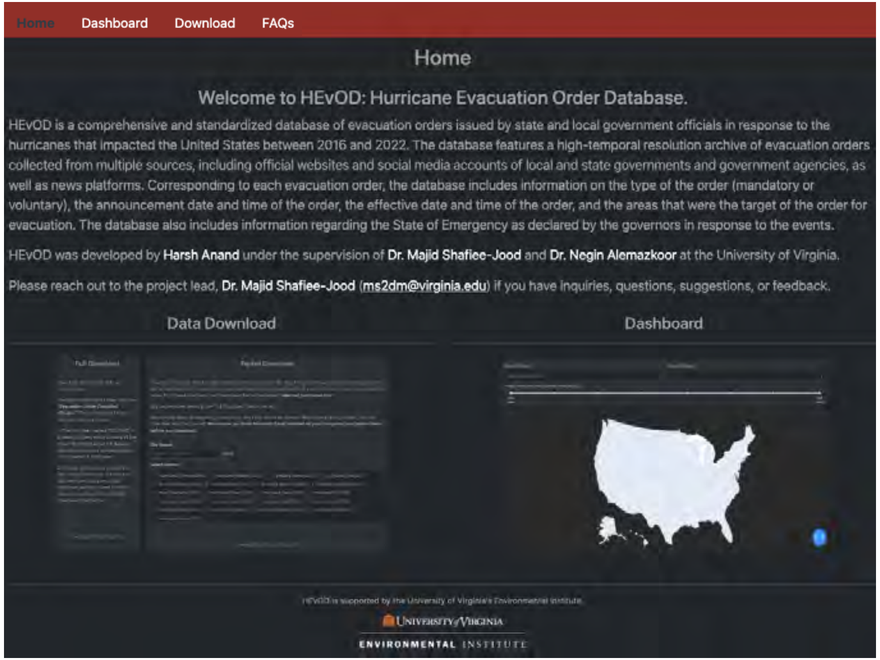
Total number of mandatory evacuation orders issued by each county

Task 1

HEvOD Dataset and Dashboard

HEvOD Dataset

https://www.HurrEvacOrder.info/



HEvOD Dashboard for visualization and data downloading

HEvOD Publication and Media


scientific data

Explore content ⌄ About the journal ⌄ Publish with us ⌄

nature › scientific data › data descriptors › article

Data Descriptor | Open access | Published: 05 March 2024

HEvOD: A database of hurricane evacuation orders in the United States

Harsh Anand, Negin Alemazkoor & Majid Shafiee-Jood

Scientific Data 11, Article number: 270 (2024) | Cite this article

1228 Accesses | 17 Altmetric | Metrics

Abstract

Assessing and improving the effectiveness of evacuation orders is critical to improving hurricane emergency response, particularly as the frequency of hurricanes increases in the United States. However, our understanding of causal relationships between evacuation orders and evacuation decision-making is still limited, in large part due to the lack of standardized, high-temporal-resolution data on historical evacuation orders. To overcome this gap, we developed the Hurricane Evacuation Order Database (HEvOD) – a comprehensive database of hurricane evacuation orders issued in the United States between 2014 and 2022. The database features evacuation orders that were systematically retrieved and compiled from a wide range of resources and includes information on order type, announcement time, effective time, and evacuation area. The rich collection of attributes and the resolution of the data in the database will allow researchers to systematically investigate the impact of evacuation orders, as a vital public policy instrument, and can serve as an important resource to identify gaps in current policies, leading to more effective policy design in response to hurricanes.

Nature Scientific Data

Media Announcement

Introduction and Motivation

Literature Review

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Research Tasks

Task 1: Evacuation Order Database

Task 2: Evacuation Order Effectiveness

Task 3: Communities Evacuation Behavior

Task 4: Cross-Hurricane Disparity

Conclusion and Future Work

Task 2

Evacuation Order Related Research

A **statistically significant predictor** of evacuation behavior in empirical and behavioral studies *[Baker, 1991, Thompson et al., 2017, Bowser, 2015, Martin et al., 2020]*

Substantial evidence suggests that households receiving evacuation orders are **more likely to evacuate** when a hurricane is approaching *[Whitehead, 2020, Thompson et al., 2017, Bowser, 2015, Mazumder et al.., 2018]*

Potential **reasons for non-compliance** with evacuation orders *[Dow and Cutter, 1998, Thiede et al., 2013, Reininger et al., 2013, Ling et al.., 2021]*

No **quantitative understanding** of the relationship between evacuation orders and evacuation behavior

Task 2

Research Questions

How effective are hurricane evacuation orders?

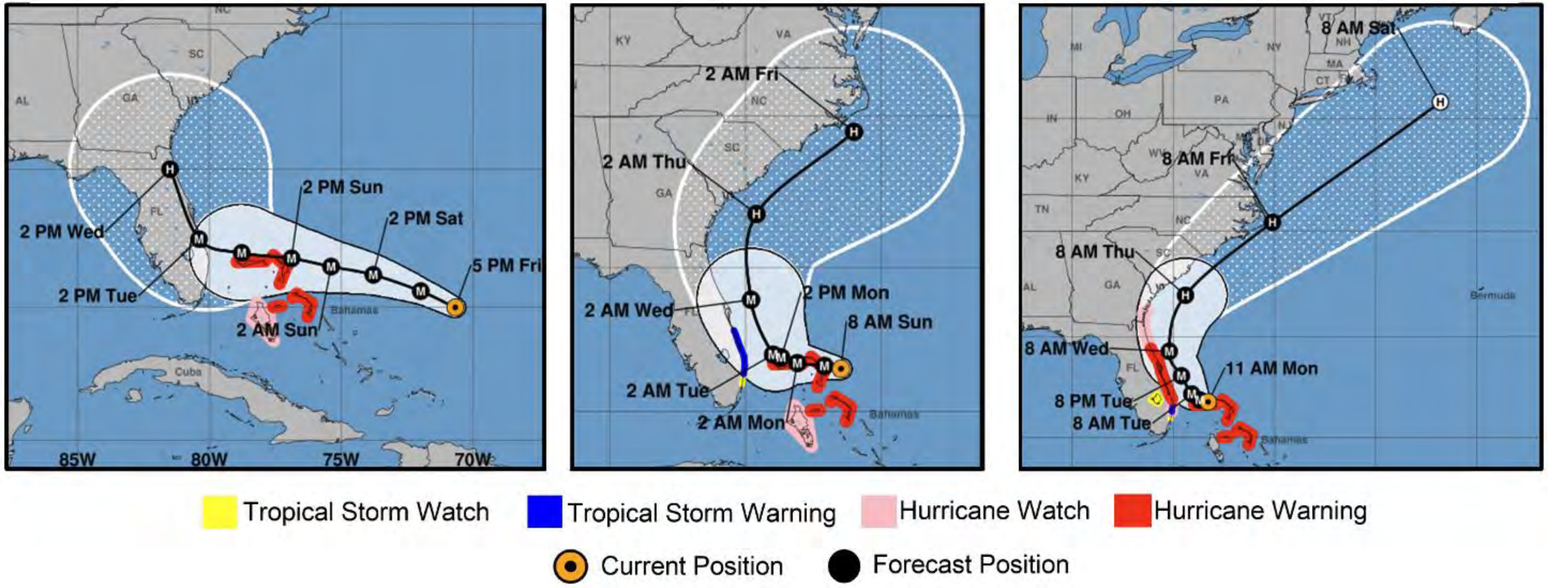
Whether evacuation decisions of communities depend on government-issued evacuation orders?

To what extent did evacuation orders influence evacuation behavior?

Task 2

Hurricane Dorian

- Category 5 Atlantic Hurricane (24th Aug – 7th Sept 2019)
- In Florida, 12 counties (~600k people) got evacuation orders



Task 2

Data Sources: Mobility Data

- spectus: Location intelligence and measurement company
- Dates: August 1st to October 31st, 2019
- Includes 11,382 census block groups (CBGs) across Florida
- Data fields:
  - Local event date
  - CBG unit number
  - Evacuated devices (or evacuee)
  - Total devices

Evacuation Index

Data Sources: Evacuation Zones and Orders

Determine which area in Florida was under an evacuation order

Evacuation Zone Shape Files

County	Issued Timestamp	Order Date	Regions	Underlying Zones
Brevard	8/30/19 17:50	8/30/19	Barrier islands, low-lying and flood-prone areas	A, B, C
Martin	8/30/19 20:05	8/30/19	Barrier islands and Zones A and B	A, B
Palm beach	9/1/19 09:30	9/1/19	Zones A and B	A, B
Indian River	9/1/19 11:25	9/1/19	Residents east of U.S. Highway 1	A, B
St. Johns	9/1/19 13:45	9/1/19	Zones A and B	A, B
Volusia	9/1/19 14:20	9/1/19	Residents on the beachside, in low-lying areas, and in RVs and mobile homes	A, BC
St. Lucie	9/1/19 15:30	9/1/19	Mobile homes, low-lying areas and on the barrier island	A, B
Nassau	9/1/19 17:00	9/1/19	Zones A, C and F	A, C, F
Duval	9/1/19 17:10	9/1/19	Zones A and B and low-lying areas	A, B
Flagler	9/1/19 22:40	9/1/19	Nursing homes, assisted living facilities, and group homes within zones A, B, and F, and flood-prone areas.	A, B, F
Putnam	9/2/19 13:00	9/2/19	Evacuation zone A, persons in low-lying areas living on boats, recreational vehicles, and mobile homes.	A, B
Clay	9/2/19 15:00	9/2/19	Zones A and B and low-lying areas, and vulnerable housing	A, B

List of mandatory evacuation orders sent out in Florida counties during Hurricane Dorian. Compiled from HEvOD.

Methodology

Data Sources

Mobility Data
Daily evacuation pattern aggregated at CBG level collected from smartphone devices

Evacuation Zones Data
Delineated areas that need to be evacuated during hurricanes largely because being susceptible to flooding and storm surge

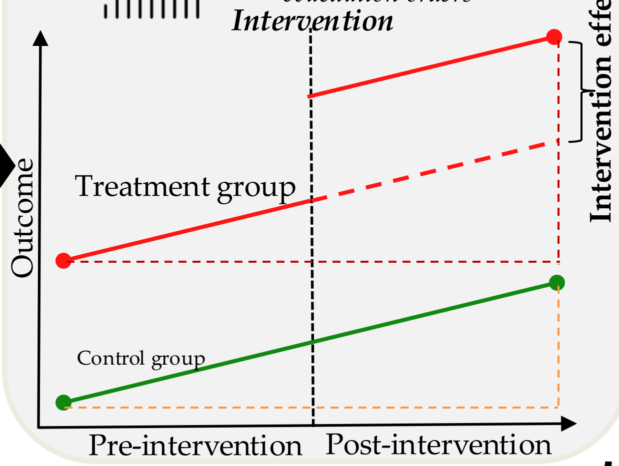
KNOW YOUR ZONE

Evacuation Orders Data
Mandatory evacuation orders issued at the county level

Methods

Geospatial Mapping
Mapping evacuation zones onto CBGs

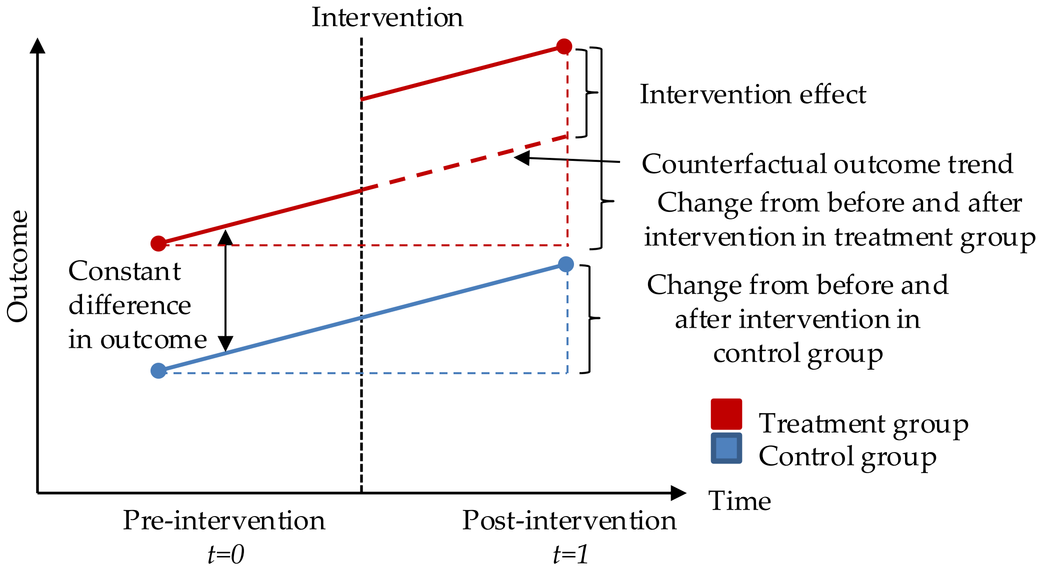
Causal Analysis
Analyze the effectiveness of the evacuation orders



Hurricane Dorian + **Florida**

Empirical Approach

Difference-in-Differences Approach



Let,

$Y(i,t)$ outcome of interest for community i at time t

$D(i,t) = 1$, if community i has been exposed to the intervention previous to period t, else 0

$$DID = \mathbb{E}\left[Y(i,1) - Y(i,0) \mid \underbrace{D(i,1) = 1}_{\text{Treatment Group}}\right] - \mathbb{E}\left[Y(i,1) - Y(i,0) \mid \underbrace{D(i,1) = 0}_{\text{Control Group}}\right]$$

Task 2

Empirical Approach (Cont.)

Two-Way Fixed Effect (TWFE)

$$Y_{it} = \alpha_i + \mu_{ct} + \sum_{j=-T}^{T} \boxed{\beta_j} D_{it}^{j} + \varepsilon_{it}$$

The average effect of evacuation orders on outcome *j* days since the order has been issued in the treated group (ATT – average treatment on treated)

Y_{it} : outcome of interest for CBG *i* in day *t*
α_i : CBG fixed effect (varies across CBG but not over time within a CBG)
μ_{ct} : county-by-day fixed effect (may vary day by day)
j : number of days since the evacuation order has been issued in CBG *i*
D_{it}^{j} : is 1 if CBG *i* in day t, CBG is j days past the evacuation order date
ε_{it} : error term

Staggered DID [Callaway et al., 2021]

$$ATT(g,t) = \mathbb{E}[Y_{i,t} - Y_{i,g-1} | G_i = g] - \mathbb{E}[Y_{i,t} - Y_{i,g-1} | G_i = C]$$

g : first period when group G_i received the evacuation order and became treated
$Y_{i,g-1}$: potential outcome in the period before group G_i is treated
C : includes CBG that were never treated

Event-study-type estimator for *l* days after evacuation order

$$ATT_l = \sum_g \omega_g ATT(g, g+l)$$

ω_g : cohort-specific weight

Task 2

CBG Identification

CBG Shape Files

Evacuation Zone Shape Files

GIS Mapping

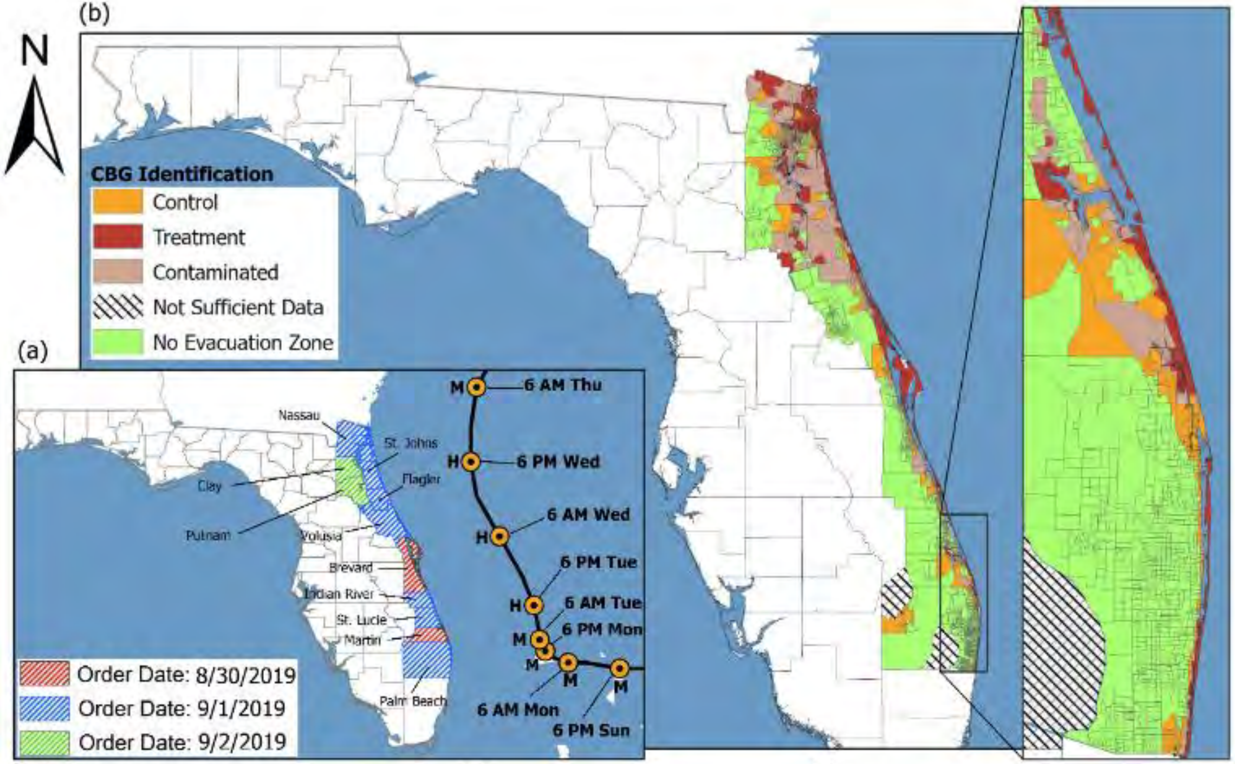
CBG Number	County	A	B	BC	C	D	DE	E	Mandatory Evacuation Zone %	Group
120090601011	Brevard	16.3	18.27	0	31.88	14.13	0	15.04	66.45	Treatment
120090601012	Brevard	5.84	26.62	0	25.06	9.01	0	7.89	57.52	Treatment
120090601013	Brevard	10.05	24.31	0	26.27	2.56	0	5.35	60.63	Treatment
120090601021	Brevard	0	0	0	0	0	0	4.09	0	Control
120090603002	Brevard	9.54	18.01	0	17.89	3.85	0	8.98	45.44	Contaminated

Mapping Matrix

County	Total CBGs	Control CBGs		Contaminated CBGs		Treatment CBGs		CBGs with No Evacuation Zone		CBGs with Insufficient Mobility Data	
		Count	*%*	*Count*	*%*	*Count*	*%*	*Count*	*%*	*Count*	*%*
Brevard County	317	45	14.2	50	15.8	94	29.7	127	40.1	1	0.3
Clay County	81	19	23.5	26	32.1	17	21.0	18	22.2	1	1.2
Duval County	489	111	22.7	125	25.6	82	16.8	171	35.0	0	0.0
Flagler County	51	8	15.7	7	13.7	18	35.3	18	35.3	0	0.0
Indian River County	92	12	13.0	4	4.3	30	32.6	46	50.0	0	0.0
Martin County	93	25	26.9	37	39.8	8	8.6	22	23.7	1	1.1
Nassau County	39	2	5.1	10	25.6	23	59.0	4	10.3	0	0.0
Palm Beach County	885	115	13.0	25	2.8	60	6.8	683	77.2	2	0.2
Putnam County	61	3	4.9	19	31.1	7	11.5	31	50.8	1	1.6
St. Johns County	81	3	3.7	29	35.8	46	56.8	2	2.5	1	1.2
St. Lucie County	140	0	0.0	17	12.1	21	15.0	102	72.9	0	0.0
Volusia County	288	13	4.5	27	9.4	127	44.1	121	42.0	0	0.0
Total	**2617**	**356**	**13.6**	**376**	**14.4**	**533**	**20.4**	**1345**	**51.4**	**7**	**0.3**

CBG Identification Count

CBG Identification (Cont.)



CBGs highlighted by (a) Order date, and (b) CBG identification.

Causal Effect Analysis Results Overview

- Main Analysis:
  - Staggered DID – considers Treatment and Control
    - Aggregated across CBGs
    - Based on order dates
- Evidence: Staggered DID – considers Control and No Zone
    - Aggregated across CBGs
    - Based on order dates
- Robustness Analysis:
  - TWFE: Aggregated across CBGs and Based on order dates
  - Staggered DID with modified control (includes Contaminated CBGs)

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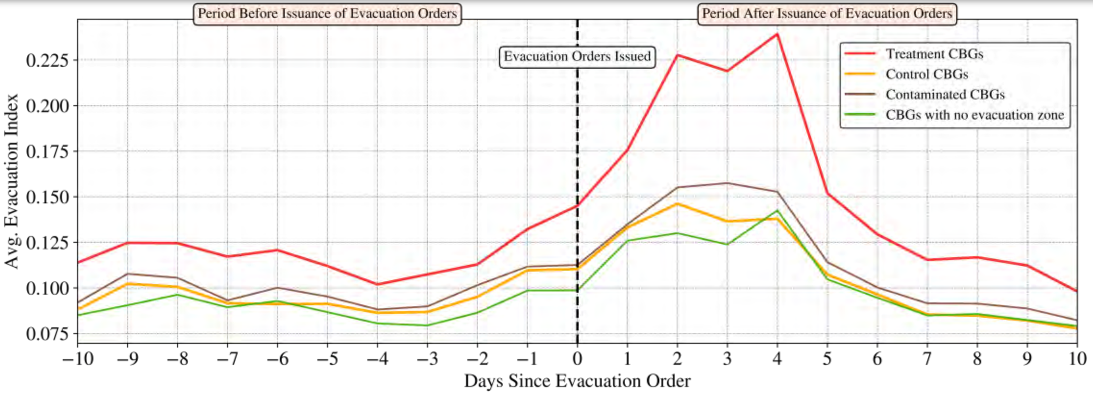
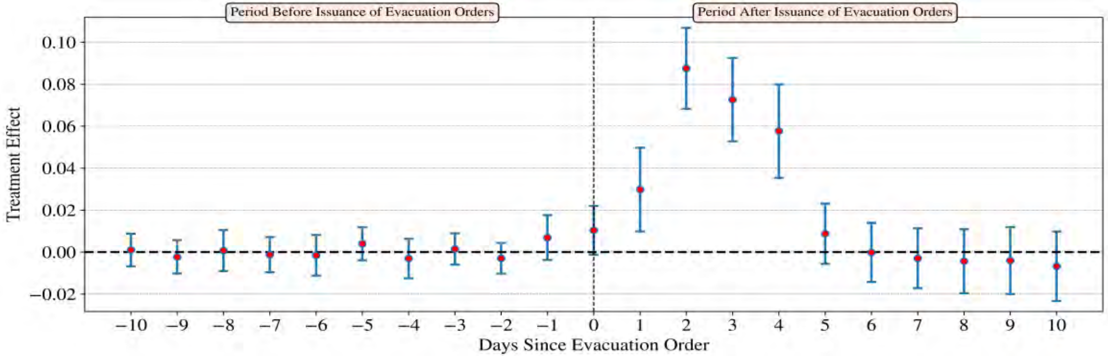
Task 2

Aggregated across CBGs



Aggregated Mobility Pattern



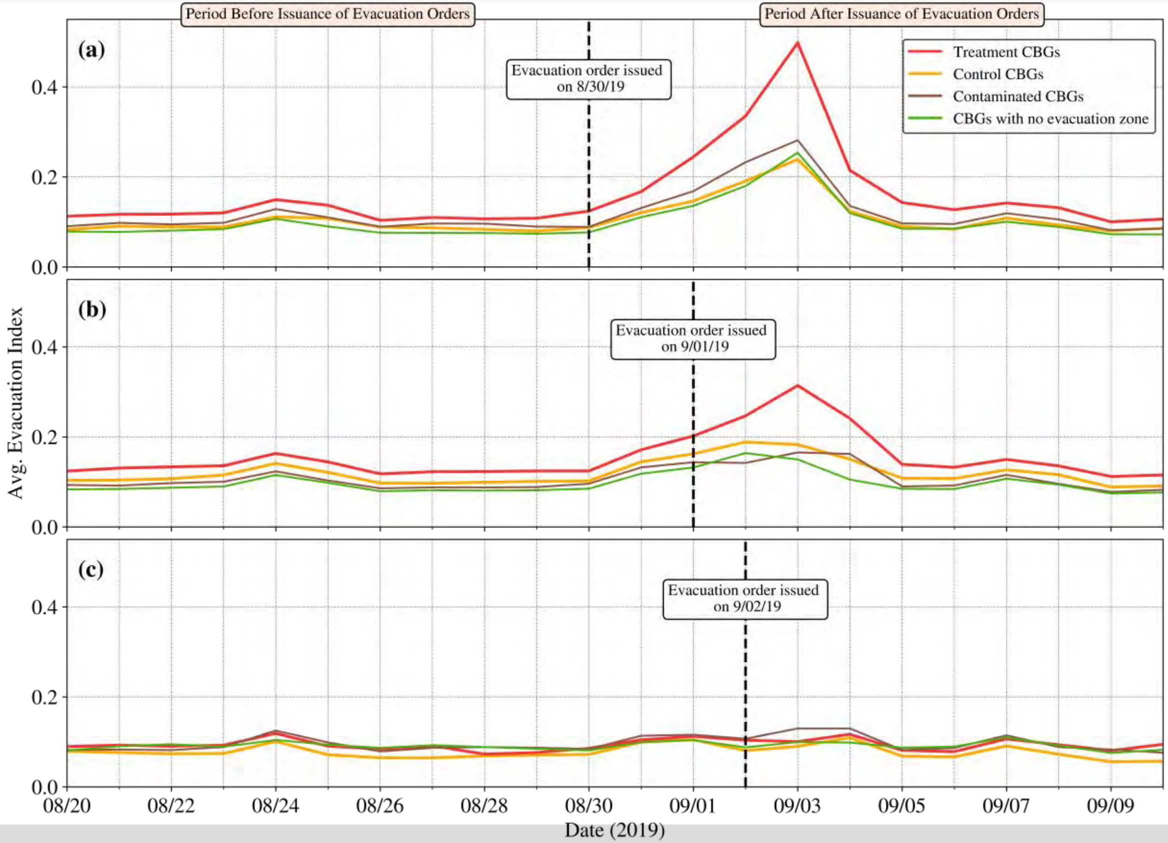
Staggered DID Treatment Effect

Event time from -17 to -1		Event time from 0 to 16	
$ATT(-17)$	−0.006 (0.006)	$ATT(0)$	0.010 (0.004)
$ATT(-16)$	0.003 (0.003)	$ATT(1)$	0.030 (0.006)
$ATT(-15)$	−0.002 (0.004)	$ATT(2)$	0.088 (0.007)
$ATT(-14)$	0.000 (0.003)	$ATT(3)$	0.073 (0.006)
$ATT(-13)$	−0.005 (0.003)	$ATT(4)$	0.058 (0.008)
$ATT(-12)$	0.002 (0.002)	$ATT(5)$	0.009 (0.005)
$ATT(-11)$	0.002 (0.002)	$ATT(6)$	0.000 (0.005)
$ATT(-10)$	0.001 (0.002)	$ATT(7)$	−0.003 (0.004)
$ATT(-9)$	−0.002 (0.002)	$ATT(8)$	−0.004 (0.005)
$ATT(-8)$	0.001 (0.003)	$ATT(9)$	−0.004 (0.005)
$ATT(-7)$	−0.001 (0.003)	$ATT(10)$	−0.007 (0.005)
$ATT(-6)$	−0.002 (0.004)	$ATT(11)$	−0.007 (0.005)
$ATT(-5)$	0.004 (0.002)	$ATT(12)$	−0.005 (0.005)
$ATT(-4)$	−0.003 (0.003)	$ATT(13)$	−0.006 (0.005)
$ATT(-3)$	0.001 (0.002)	$ATT(14)$	−0.006 (0.005)
$ATT(-2)$	−0.003 (0.002)	$ATT(15)$	0.002 (0.006)
$ATT(-1)$	0.007 (0.003)	$ATT(16)$	−0.003 (0.006)

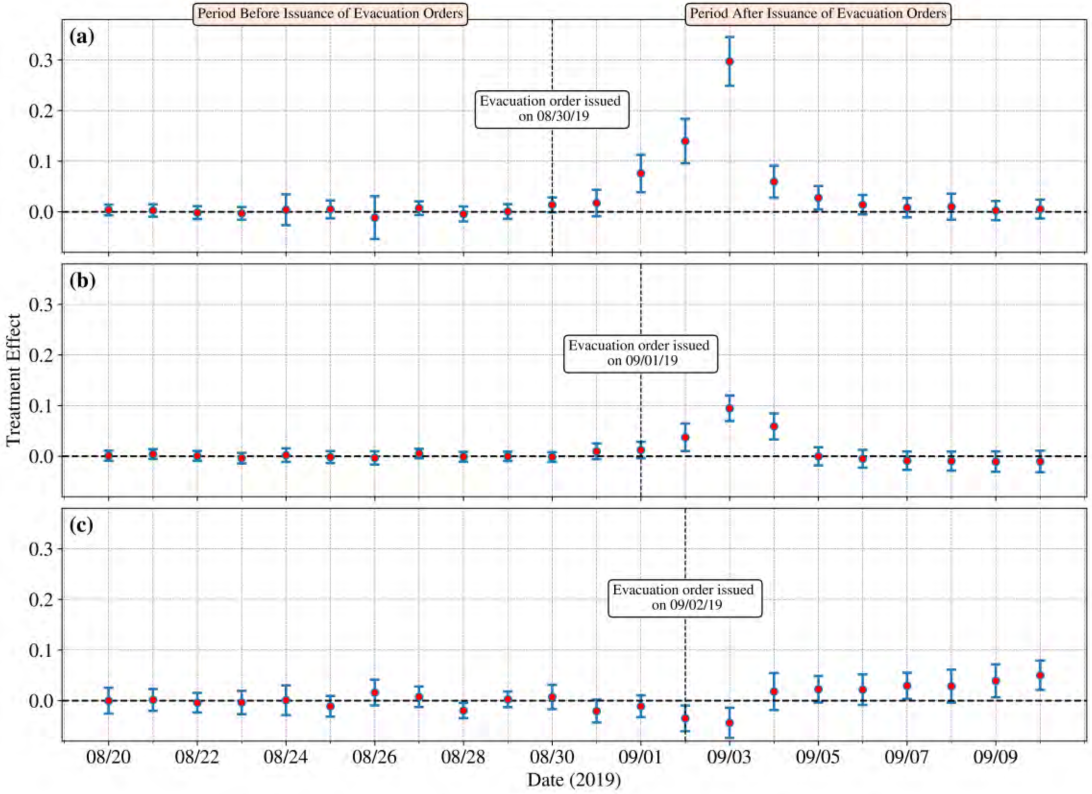
Num. Obs.: 27,854
CBGs considered: 889 (Treatment: 533, Control: 356)

Staggered DID Regression Coefficients

Mobility Pattern for Three Order Dates CBGs



Staggered DID Result for Three Order Dates CBGs



Conclusions

- Evacuation orders have a statistically significant effect on increasing evacuation rates, with an overall treatment effect of about 8% points
- Significant variations across groups of counties that received orders on different days
- Shadow evacuation during Hurricane Dorian in Florida was not significant

Task 2

Publication (Under Review)

Harsh Anand, Mani Rouhi Rad, Negin Alemazkoor, and Majid Shafiee-Jood. "Unveiling the Truth: How Effective are Hurricane Evacuation Orders? Insights from Hurricane Dorian in Florida." Currently UNDER REVIEW at ***Bulletin of the American Meteorological Society***.

Harsh Anand

Dr. Mani Rouhi Rad

Dr. Negin Alemazkoor

Dr. Majid Shafiee-Jood

Task 3

Research Question

Examine how socio-economic and demographic factors affect the evacuation decisions of communities in response to evacuation orders

Methodology

Data Sources

Mobility Data
Location-based evacuation data per CBG for each day

Evacuation Zones Data
Official split of areas vulnerable to storm surge used by local/state emergency managers to direct order

Evacuation Orders Data
The historic evacuation orders issued by the government officials

Socio-demographic Data
5-year estimate of American Community Survey about gender, age, income, and ethnicity characteristics of the US

SAFEGRAPH

Causal Inference

Causal Analysis
Analyze the effectiveness of the evacuation orders

Statistical Significance
The average percentage of evacuation caused due to evacuation orders

Feature Extraction

ML-based Feature Analysis
Analyze the socio-demographic factors contributing to compliance with evacuation orders

Community Pattern Factors
The key factors contributing to the variations in evacuation rates across different community population

Hurricane Dorian + **Florida**

Task 3

Causal Effect Analysis

Difference-in-Differences Approach

Linear parametric model:

$$Y(i,t) = \mu + \tau D(i,1) + \gamma t + \alpha D(i,t) + \epsilon(i,t)$$

$Y(i,t)$ is the output of community i at time t

μ is the constant factor

τ group-specific time-invariant effect

γ time effect

α is intervention effect

$\epsilon(i,t)$ are unobservable characteristics of the individual

Least squares estimator of α can be estimated as:

$$\alpha = \{\mathbb{E}[Y(i,1)|D(i,1)=1] - \mathbb{E}[Y(i,1)|D(i,1)=0]\} - \{\mathbb{E}[Y(i,0)|D(i,1)=1] - \mathbb{E}[Y(i,0)|D(i,1)=0]\}$$

Task 3

Causal Effect Regression Result

Regression Analysis

	coef	std err	t-value	P>|t-value|
(Intercept)	0.069	0.002	33.446	0.000
$D(i,1)$	0.047	0.004	11.469	0.000
t	0.019	0.003	6.460	0.000
$D(i,t)$	$\boxed{0.082}$	0.006	14.184	0.000

Regression Result

Socio-economic and Demographic Feature Association

CBGs Behavior Split

CBG evacuation behavior

- Highly compliant (>9.3%)
- Minimally compliant (<9.3%)

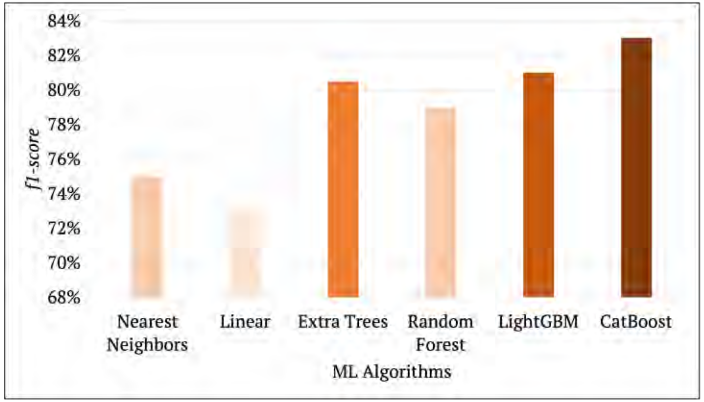
County	Highly-compliant	Mildly-compliant
Brevard	84	8
Clay	0	17
Duval	12	67
Flagler	10	8
Indian River	22	5
Martin	8	0
Nassau	15	8
Putnam	0	7
Palm Beach	17	33
St. Johns	34	12
St. Lucie	13	7
Volusia	45	77
Total	**260**	**249**

* Does not include CBGs with insufficient data.

Features Considered During Modeling

- Socio-economic & demographic features* *(36 features)*
- Other binary features
  - Zone A
  - Coastal county
  - Order-Lead-Time

Socio-economic and Demographic Feature Modeling

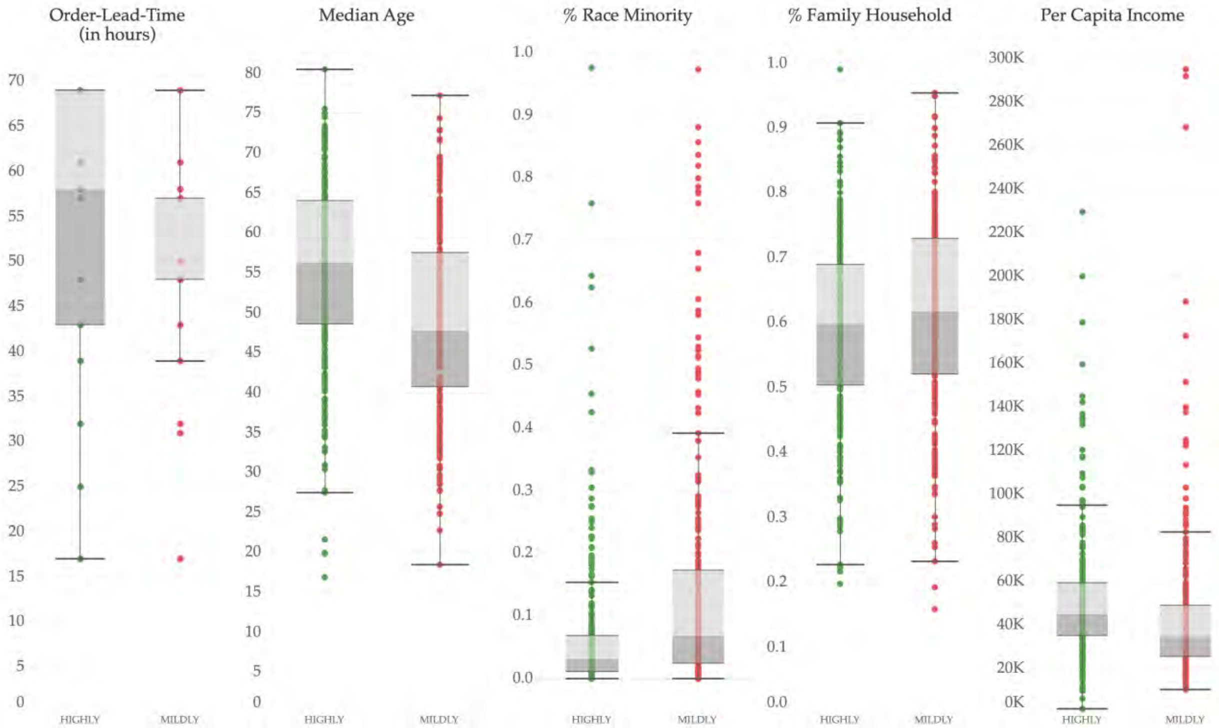


Machine Learning Model Performance

Features	CatBoost	LightGBM	Extra Trees	Relevance
Order-Lead-Time				High
Median Age				
Zone A				
Percent Race Minority				
Percent Family Household				
Per Capita Income				
Percent Households Internet Access				
Percent Households No Computer				
Coastal County				Low

Relevant Features

Significant Socio-economic and Demographics Factors



Boxplot of significant socio-economic and demographic factors for CBGs with highly- and mildly-compliant evacuation.

Conclusions

- Early evacuation orders in relation to the Order-Lead-Time of the hurricane relate to higher evacuation after the order.
- CBGs with younger median age and higher racial minority populations should be looked at closely
- CBGs with Zone A experience higher evacuation than CBGs without Zone A

Task 3

Publication

Conferences > 2023 57th Annual Conference o...

Perspicuity of Evacuation Behavior in Communities during Hurricanes using Large-scale Mobility Patterns and Communal Characteristics

Publisher: IEEE

Cite This

PDF

Harsh Anand ; Majid Shafiee-Jood ; Negin Alemazkoor **All Authors**

Harsh Anand

Dr. Majid Shafiee-Jood

Dr. Negin Alemazkoor

Introduction and Motivation

Literature Review

Research Objectives

Research Tasks

Task 1: Evacuation Order Database
Task 2: Evacuation Order Effectiveness
Task 3: Communities Evacuation Behavior

Task 4: Cross-Hurricane Disparity

Conclusion and Future Work

Task 4

Existing Income and Race Disparity Literature

Relationship with Evacuation Decision

Survey and Interviews, and Social Media Data	Mobility Data
• **Income:** Positive, Negative, and No Correlation • **Race:** Significant and Insignificant Predictors	• **Income:** Positive, and Negative (1) • **Race:** Significant
Variations in Disparity Findings	**Consistent Disparity Findings**

Findings are **limited** in terms of **comparability** and **generalizability**

Examines Single Case

Employs Distinct Study Design

Selection of Study Areas

Task 4

Research Questions

If a consistent study design is applied, would we be able to reach a **general conclusion** on how race and income impact evacuation behavior?

To what extent do different **study designs** cause these variations?

Hurricanes Consideration

Hurricane	State	Start Date	End Date
Florence	North Carolina	August 31, 2018	September 17, 2018
Florence	South Carolina	August 31, 2018	September 17, 2018
Florence	Virginia	August 31, 2018	September 17, 2018
Dorian	Florida	August 24, 2019	September 10, 2019
Dorian	North Carolina	August 24, 2019	September 10, 2019
Dorian	South Carolina	August 24, 2019	September 10, 2019
Laura	Louisiana	August 20, 2020	August 29, 2020
Laura	Texas	August 20, 2020	August 29, 2020
Sally	Louisiana	September 11, 2020	September 14, 2020
Delta	Louisiana	October 4, 2020	October 10, 2020
Ida	Louisiana	August 26, 2021	September 5, 2021
Ida	Mississippi	August 26, 2021	September 5, 2021
Ian	Florida	September 23, 2022	September 30, 2022

- Comparison across 7 hurricanes
- 12 hurricane cases - across 6 states

Methodology

Data Sources

Mobility Data
Daily evacuation pattern aggregated at CBG level collected from smartphone devices

Evacuation Zones Data
Delineated areas that need to be evacuated during hurricanes largely because being susceptible to flooding and storm surge

Evacuation Orders Data
Mandatory evacuation orders issued at the county level

Geospatial Mapping
Mapping evacuation zones onto CBGs

Income and Racial Categories

Income

Race

High/Low Income	High/Low Minority

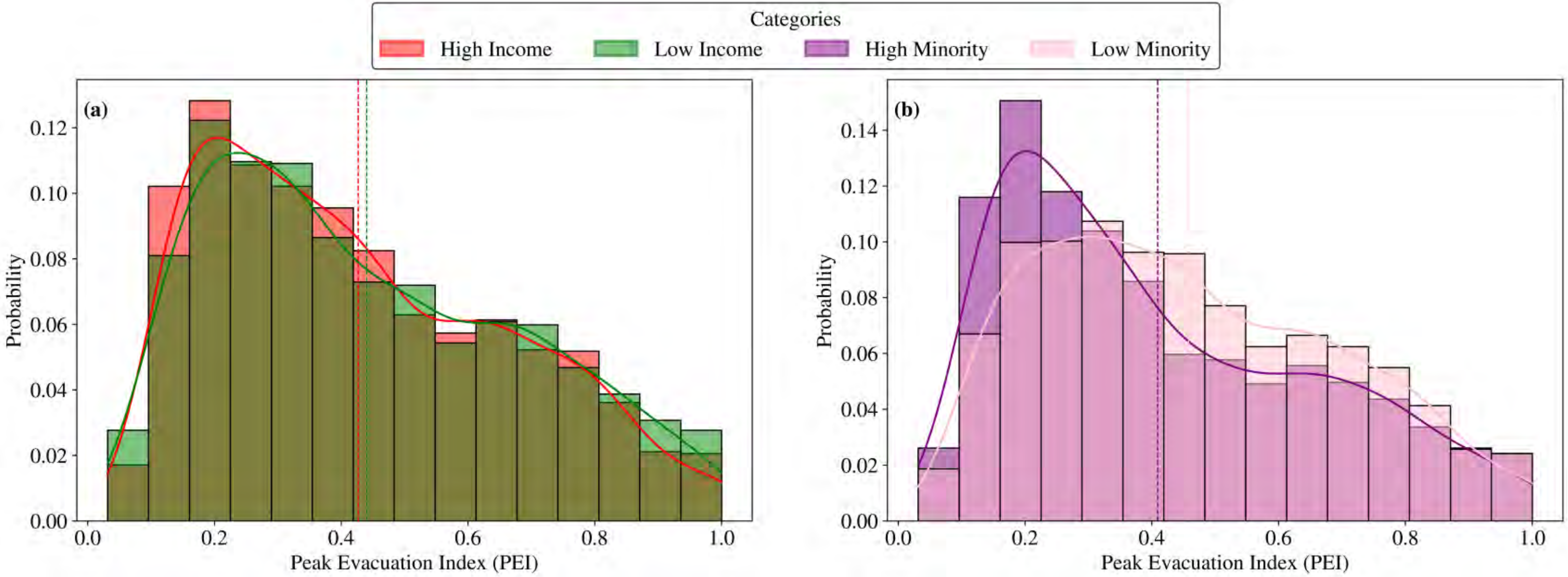
Category Definition

Median Value	Median Value

Across Multiple Hurricanes

Across Multiple States

Income and Race Disparity Across All Hurricanes



No significant statistical difference

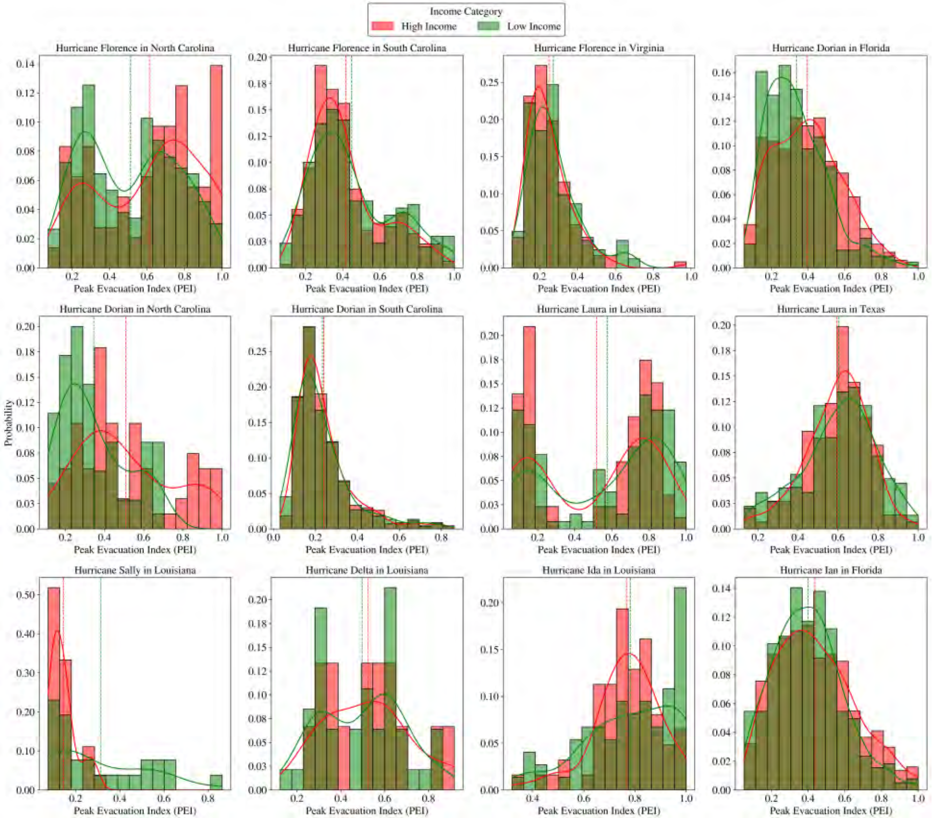
No significant statistical difference

Task 4

A Closer Look at Income Disparity

Variety of Patterns Across Hurricanes

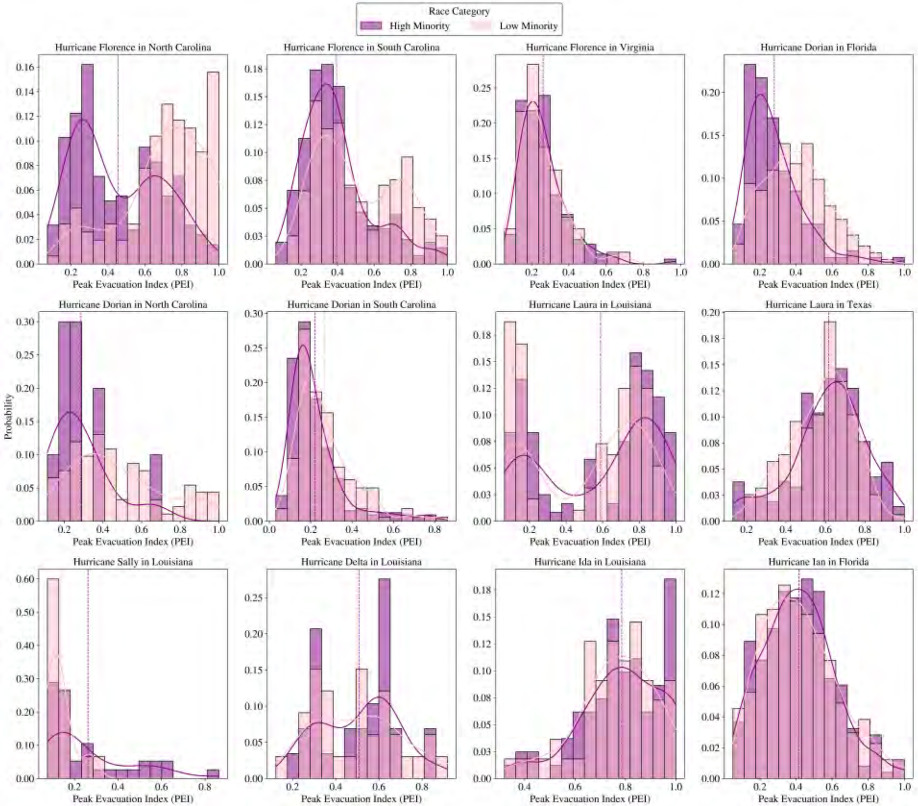
- **Seven** cases reveal **no significant** statistical differences in evacuation rates.
- In **five** cases, **significant** differences emerge
  - In **four** instances, High-Income groups had higher average PEIs
  - In **one** case, Low-Income CBGs had significantly higher average PEI



A Closer Look at Race Disparity

Variety of Patterns Across Hurricanes

- **Six** cases reveal **no significant** statistical differences in evacuation rates.
- In **six** cases, **significant** differences emerge
  - In **five** instances, Low-Minority groups had higher average PEIs
  - In **one** case, High-Minority CBGs had significantly higher average PEI



Methodology

Data Sources

Mobility Data
Daily evacuation pattern aggregated at CBG level collected from smartphone devices

Evacuation Zones Data
Delineated areas that need to be evacuated during hurricanes largely because being susceptible to flooding and storm surge

Evacuation Orders Data
Mandatory evacuation orders issued at the county level

Geospatial Mapping
Mapping evacuation zones onto CBGs

Income and Racial Categories

Income — High/Low Income

Race — High/Low Minority

Category Definition

External Definition | Over 0%

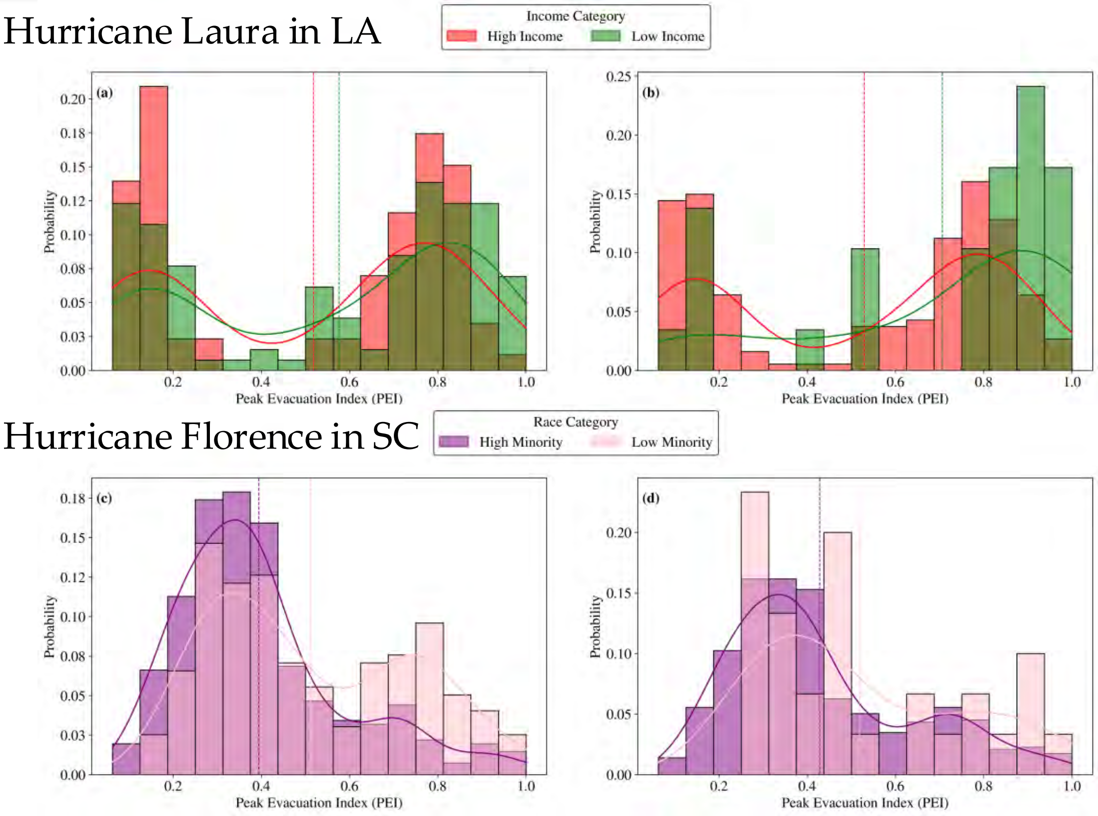
Across Multiple Hurricanes

Across Multiple States

Impact of Study Design: Change in Definition

Significant Shift Seen Across

- Income: Non-significant disparities shifted to being significant
- Race: Shift from significant to non-significant disparities



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Geospatial Mapping

Mapping evacuation zones onto CBGs

Income and Racial Categories

Income	Race
High/Low Income	High/Low Minority

Category Definition

Median Value	Median Value

Across Multiple Hurricanes

Across Multiple States

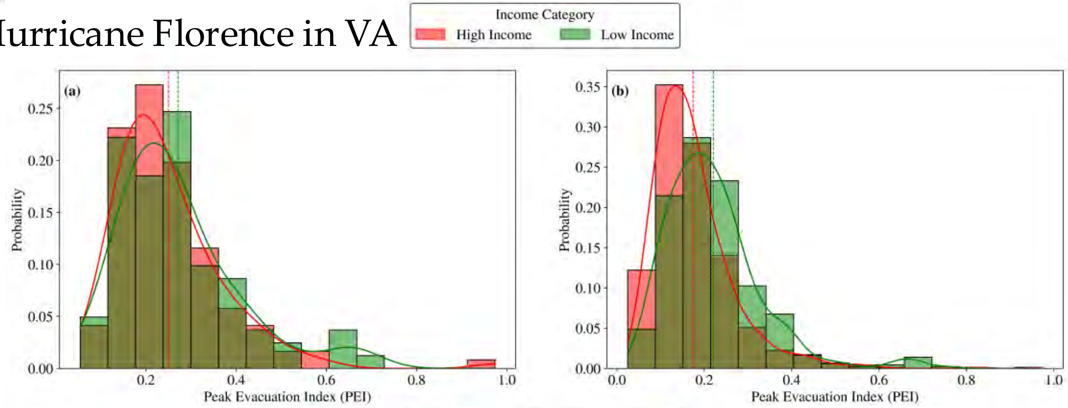
Include all CBGs in the counties affected by evacuation orders.

Impact of Study Design: Change in Boundary of Focus Area

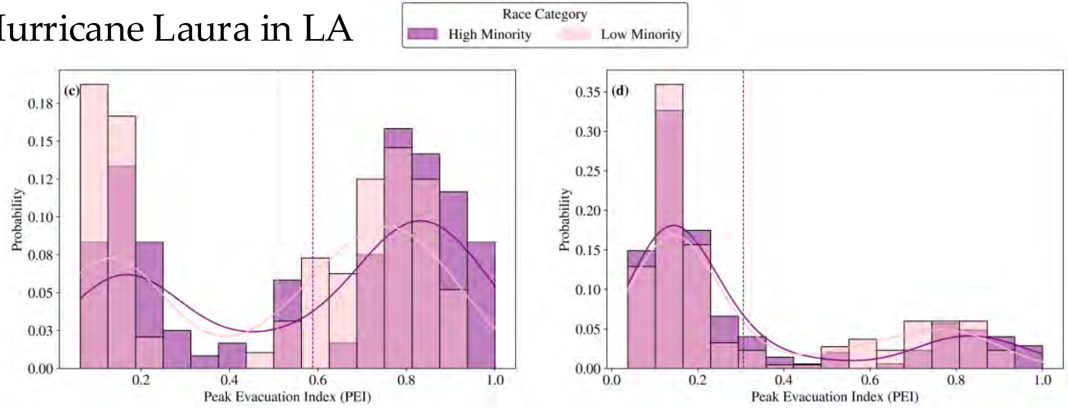
Significant Shift Seen Across

- Income: Non-significant disparities shifted to being significant
- Race: Shift from significant to non-significant disparities

Hurricane Florence in VA



Hurricane Laura in LA



Conclusions

- Systematically evaluated income and racial disparities in communities affected by multiple hurricanes
- Disparities in evacuation among different socioeconomic groups vary case by case
- Study design significantly impacts the observed trends within a single case

Publication (Accepted)

Harsh Anand, Samarth Swarup, Majid Shafiee-Jood, and Negin Alemazkoor. "Understanding of income and race disparities in hurricane evacuation is contingent upon study case and design." Manuscript ACCEPTED at ***Nature Scientific Report***.

Harsh Anand

Dr. Samarth Swarup

Dr. Majid Shafiee-Jood

Dr. Negin Alemazkoor

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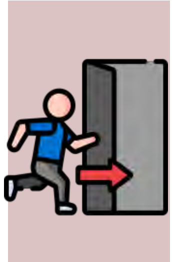
Contributions

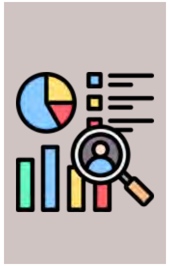
- A comprehensive, high-temporal-resolution **repository of evacuation orders**
- Investigated the **causal relationship** between mandatory evacuation orders and observed community mobility patterns, using high-fidelity mobility data
- Explores how **socioeconomic and demographic factors** affect the evacuation decisions of communities
- Explore **disparity variations** by comparing evacuation patterns across multiple hurricanes

Broader Impact

Informing Policy & Advancing Research

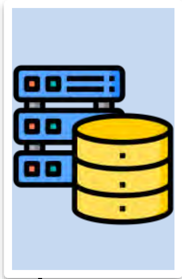


Enhanced Understanding & Improved Strategies



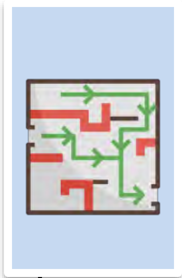
Addressing Disparities to Create Inclusive Evacuation Frameworks

Future Plans



Advance HEvOD

Expand Evacuation Order Effectiveness Analysis



Evaluate Policies related to Evacuation Zones

Thank you!

Stay connected with SERC Online:

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