

Two Faces of Wind Vulnerability: Structural Fragility and Economic Exposure in Coastal Louisiana

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Research Article

Keywords: wind vulnerability, environmental justice, coastal Louisiana, structural damage, coastal sorting

Posted Date: September 14th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9666056/v1>

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Abstract

Environmental justice research on hurricanes has focused primarily on flooding, leaving wind hazards comparatively understudied despite their substantial economic impacts. Whether wind vulnerability follows similar social patterns remains empirically unclear. This study addresses this gap by integrating building-level probabilistic wind damage modeling with census tract sociodemographic data across 708 tracts in coastal Louisiana. Spatial lag regression models are used to examine associations between Expected Annual Structural Damage (EASD) and Expected Annual Damage in Dollars (EADD) and key sociodemographic characteristics, including racial composition, income, housing tenure, and rurality.

Results indicate that wind vulnerability reflects two distinct dimensions. Rural residence and renter concentration are significantly associated with both EASD and EADD, consistent with a structural vulnerability pattern. Median household income is more strongly associated with EADD than with EASD, reflecting differences in economic exposure linked to the spatial concentration of higher-value assets. Racial composition variables are not statistically significant for either outcome, with the exception of the proportion of non-Hispanic residents of other races, which is associated with EADD.

These findings suggest that wind-related vulnerability in coastal Louisiana may not align with the racialized exposure patterns commonly documented in flood-focused environmental justice research and underscore the value of hazard-specific analyses that distinguish between physical and economic dimensions of risk.

1. Introduction

1.1 Overview

Louisiana has experienced economic losses, totaling between \$210–320 billion since 1980, attributed to tropical cyclones and severe storms (NCEI, 2023). Approximately 45% of census tracts in Louisiana are designated as high to relatively high-risk areas for natural hazards (FEMA National Risk Index (NRI)), with 50% being disadvantaged communities (Climate & Economic Justice Screening Tool), encompassing 2.3 million Louisianians. The state ranks third in the nation for wind-related insurance, with premiums substantially exceeding the national average, particularly in hurricane-exposed coastal regions (Insurance Information Institute, 2024; ValuePenguin, 2024). This financial burden falls unevenly, and the question of which communities bear the greatest exposure, and why, sits at the heart of environmental justice research on natural hazards.

Environmental justice research focuses on how environmental risks and benefits are distributed, especially whether low-income populations, communities of color, and other marginalized groups face greater exposure. When applied to hurricanes, this work consistently shows that flooding tends to concentrate in socially vulnerable communities, shaped by long-standing factors such as historical segregation, discriminatory housing policies, and uneven infrastructure investment (Chakraborty et al. 2019; Smiley 2020). What remains less clear is whether wind hazards follow a similar pattern or if they

create a different pattern of social inequality in risk, leaving a critical gap in both environmental justice research and disaster policy.

1.2 Environmental Justice and Hurricane Wind Vulnerability

Environmental justice examines how environmental hazards and benefits distribute across populations, particularly whether marginalized groups face disproportionate exposure. As part of a broader body of work that analyzes social vulnerability (Cutter et al., 2000), much of the quantitative spatial research examining disparities in levels of disaster risk or impacts concerns flooding (Lieberman-Cribbin et al. 2021; Shao et al. 2020). This work includes several studies that document the relationship between environmental justice variables (like the racial and class composition of the community) and greater flood risks or impacts (Chakraborty et al. 2019; Smiley 2020; Smiley et al. 2022).

But any relationship between flooding and environmental justice depends importantly on the socio-spatial context. Collins et al., (2018) showcase the importance of socio-spatial context in their study of the cases of Houston, Texas, and Miami, Florida. For Houston, flood risk maps on to environmental justice as low-lying neighborhoods are disproportionately industrial zones with more Black and Hispanic residents, but, in Miami, coastal zones are amenity-laden and tend to attract White and higher-income residents. The implication is that the extent to which flooding reflects environmental justice patterns will depend on the area and hazard under examination. In an example from Louisiana, Tama et al. (2025) finds countervailing patterns of racial inequalities in exposure from a major 2016 flood comparing an urban and suburban parish (where Black residents were disproportionately affected) to some neighboring suburban parishes (where White residents were disproportionately affected). Such evidence indicates that spatial context – in land use, population patterns, built environment and more – can condition flood risk.

These results from flooding-based EJ research are constructive, but incomplete, in helping build a framework for understanding inequalities in hurricane risk as hurricane damage results not only from flooding but also from wind. A small amount of spatial quantitative research on wind risk disparities suggests additional important dynamics. In one example, Logan and Xu (2015) analyzed the spatial extent of wind damage from all hurricanes affecting the U.S. Gulf Coast between 1950 and 2005, examining its associations with socio-demographic characteristics such as age, race, and poverty status over time. They found that while socially advantaged residents were initially concentrated along the coast, in more recent years, socially vulnerable groups, particularly the elderly, the poor, and Black residents, have shifted to areas of higher risk. In a subsequent study, Logan et al., (2016) investigated how wind damage influenced population change in Gulf Coast counties. They observed a pattern of “segmented withdrawal,” in which Whites and young adults were better able to relocate to safer areas over time compared to Blacks and the elderly.

While these studies are informative, their wind risk estimates hinge on hurricane characteristics (e.g., the location of the eye and storm intensity) without explicitly accounting for characteristics of the built

environment, particularly those of residential buildings (Logan et al. 2016). Further their focus on a wider spatial extent of wind damage (i.e., counties) overlooks differences in vulnerability within those areas. If wind risk is characterized by using methods that mask spatial heterogeneity at a higher spatial scale or structural differences across housing stock, potential inequalities may remain undetected. Consequently, evaluating the environmental justice implications of wind hazards necessitates modeling approaches that generate comprehensive wind damage estimates that account for socio-spatial contexts of land use and development (Collins et al., 2018).

Other studies have sought to combine wind damage and intensity with social vulnerability characteristics to gauge overall vulnerability to hurricanes (Bjarnadottir et al., 2011; Colavito et al., 2017; Enderami et al., 2022). While these studies provide comprehensive tools for assessing hurricane-related vulnerability, they fall short of identifying which specific sociodemographic characteristics are independently associated with wind damage and through what mechanisms.

1.3 Wind Risk Assessment Methods

Wind risk assessment has advanced significantly through engineering fragility models that estimate structural damage probability across wind speeds. These include deterministic models (Emanuel et al., 2006; Pinelli et al., 2011) and probabilistic approaches incorporating uncertainty propagation (Li & Ellingwood, 2006; Nofal, 2020). Models address diverse building types: residential (Masoomi et al., 2018), commercial (Koliou et al., 2017), and social institutions (Masoomi & van de Lindt, 2018), and increasingly consider multi-hazard interactions including surge, waves, and windborne debris (Abdelhady et al., 2020).

Regional-scale assessment tools like FEMA's HAZUS-MH integrate hazard, exposure, and fragility data to project expected annual losses. These models use probabilistic simulations of synthetic storm tracks informed by historical hurricane data to generate return period wind speed maps (Vickery et al., 2006, 2009), characterizing wind hazard directly at aggregated geographic scales (census tracts, ZIP codes, or counties) by assigning representative wind speeds to entire areas. This tract-level characterization assumes uniform exposure across all buildings within a tract, overlooking critical within-tract variations in vulnerability. For instance, buildings within the same census tract may experience substantially different wind loads depending on their specific location (coastal versus inland positions), local terrain roughness (open fields versus tree-sheltered areas), structural characteristics (newer code-compliant versus older substandard construction), and sheltering effects from neighboring structures.

Building-specific modeling improves the accuracy of tract-level damage estimates because it accounts for within-tract variation in building exposure before aggregation, rather than assigning a single representative wind speed to all structures in a tract. Yet despite these advantages, building-specific wind modeling has not been integrated with environmental justice analysis in coastal Louisiana, limiting our understanding of who faces disproportionate wind exposure.

1.4 Gaps in Existing Research

Three key limitations in existing research motivate this study.

First, environmental justice research on hurricanes has largely centered on flooding, with far less attention given to wind damage despite its substantial physical and economic impacts. Prior wind-focused work has mapped the spatial extent of hurricane wind damage across Gulf Coast regions or developed composite vulnerability indices that combine wind with other hazard components. While informative, these approaches do not isolate which sociodemographic characteristics are independently associated with wind damage exposure. As a result, it remains unclear whether wind vulnerability follows environmental justice patterns or reflects an entirely distinct set of social dynamics.

Second, commonly used regional assessment tools characterize wind hazard at aggregated geographic scales, typically assigning a representative wind speed to all buildings within a census tract or county. This practice overlooks substantial variation in exposure that can occur within the same spatial unit due to differences in building location, terrain conditions, and structural attributes. Such within-unit heterogeneity means that tract-level hazard characterization may systematically misrepresent the actual distribution of wind damage within neighborhoods, producing less accurate tract-level exposure estimates for sociodemographic analysis. Approaches that model wind damage at the individual building level before aggregating to the tract level can capture this spatial and structural variability, providing more accurate neighborhood-level damage estimates as inputs to environmental justice analysis. Yet this level of methodological detail has rarely been incorporated into environmental justice studies of wind risk in coastal Louisiana.

Third, research on wind hazards remains divided across disciplinary lines. Engineering studies have produced sophisticated probabilistic models capable of estimating building-level wind damage, but these advances have seldom been integrated with social science frameworks concerned with distributional equity. Conversely, environmental justice research has identified socially vulnerable populations but often relies on simplified hazard proxies rather than detailed damage estimates. The lack of integration between these perspectives limits our ability to understand not only where wind risk occurs, but also who experiences it and why. This study responds to that gap by combining building-level probabilistic wind damage modeling with census-based sociodemographic analysis within a spatial regression framework, offering a more comprehensive assessment of wind vulnerability in coastal Louisiana.

1.5 Objectives and Contributions

This study has three objectives. First, we test whether wind vulnerability in coastal Louisiana follows the same pattern that is documented for flooding, or reflects distinct sociodemographic patterns potentially related to coastal sorting and building quality. Second, we identify which sociodemographic characteristics are independently associated with wind damage exposure after accounting for relevant controls. Third, we assess whether EASD and EADD capture distinct dimensions of vulnerability; one reflecting physical structural performance, the other reflecting economic loss, and what this distinction reveals about the populations at risk.

In addressing these objectives, this study makes three primary contributions. First, it advances the literature by integrating building-level probabilistic wind damage modeling with environmental justice analysis, thereby moving beyond the coarse hazard proxies that have characterized much of the prior work. Second, it develops and applies a conceptual distinction between structural vulnerability and economic exposure through the joint analysis of EASD and EADD, demonstrating that the choice of outcome metric can meaningfully influence the sociodemographic patterns identified as vulnerable. Third, the findings show that wind vulnerability does not conform to a single environmental justice pattern; rather, it reflects two distinct and independent dimensions, one associated with structural fragility in rural and renter-dominated communities, and another associated with economic exposure driven by the spatial concentration of high-value assets in coastal areas.

2. Study Area

The focus of this research is on Southern Louisiana, an area highly vulnerable to coastal flooding, hurricanes, and other natural hazards. The study area, shown in Fig. 1, includes the following parishes: Ascension, Assumption, Calcasieu, Cameron, Iberia, Jefferson, Lafourche, Livingston, Orleans, Plaquemines, St. Bernard, St. Charles, St. James, St. John the Baptist, St. Martin, St. Mary, St. Tammany, Tangipahoa, Terrebonne, Vermillion. This region represents one of the most hurricane-exposed areas in the United States, encompassing a diverse range of coastal, urban, suburban, and rural communities across a pronounced sociodemographic gradient from high-income suburban parishes to low-income rural coastal parishes. Wind hazard intensity varies substantially across the study area, with the highest expected wind speeds concentrated along the southeastern shoreline and attenuating inland. The twenty parishes contain 716 census tracts under 2020 boundaries, of which 708 are included in the final analytical sample following exclusions described in Section 3.3.1

3. Methodology

3.1 Overview

This study integrates two analytical modules to examine the sociodemographic dimensions of wind vulnerability in coastal Louisiana. The first is a wind risk analysis module that generates building-level estimates of expected annual wind damage across 708,000 + residential structures in the study area. The second is a sociodemographic analysis module that tests associations between census tract-level demographic and socioeconomic characteristics and those wind damage estimates using spatial regression.

Census tracts serve as the analytical unit, providing a standardized geographic scale that aligns with available sociodemographic data while capturing local variation in exposure and vulnerability across the twenty-parish study area. Critically, wind risk metrics are modeled at the individual building level before aggregation to tracts, assigning building-specific coordinates, terrain roughness, structural

characteristics, and wind speed distributions to each structure, rather than assuming uniform wind exposure across all buildings within a tract as in standard regional assessments.

3.2 Wind Risk Module

3.2.1 Building Inventory

The building inventory for the study area was constructed using the National Structure Inventory (NSI), a dataset developed by the U.S. Army Corps of Engineers that provides location-specific information for structures across the United States (USACE, 2022). For each residential building in the twenty-parish study area, the NSI provided geographic coordinates, structural type, foundation height, and estimated structure and contents values. Because the NSI is based on 2010 Census tract boundaries, a spatial join was performed in ArcGIS to align all building locations with 2020 Census tract boundaries, ensuring consistency with the demographic data used in the sociodemographic module.

The NSI provides limited detail on construction characteristics beyond basic structural type. To address this, Monte Carlo simulation was used to probabilistically assign a full set of structural attributes to each building based on regional occupancy and construction type distributions adapted from Hazus-MH (FEMA, 2022). For each building, the simulation assigned secondary structural characteristics including roof shape, roof cover type, secondary water resistance, roof deck attachment style, and garage and shutter conditions. These secondary attributes are critical determinants of wind performance. Features such as roof deck attachment and secondary water resistance are among the most important factors distinguishing code-compliant from substandard construction.

Each building was then assigned a unique building identifier (wbID) encoding the full combination of its structural attributes. The final inventory contained several hundred unique wbIDs, each representing a distinct structural profile. This building-level heterogeneity is preserved throughout the damage estimation process, ensuring that structural variation within and across census tracts is captured in the resulting tract-level damage estimates.

3.2.2 Wind Hazard Characterization

Wind hazard was characterized at the individual building level using wind speed rasters from the ASCE Hazard Tool database. Raster layers of 3-second peak gust wind speeds were obtained for 12 return periods ranging from 10 to 1,000,000 years. For each building, the wind speed corresponding to each return period was extracted from the raster using the Extract Multi Values to Points tool in ArcGIS, linking every structure to a full spectrum of hazard intensities at its precise geographic location.

Surface roughness is a key parameter in determining wind loads and associated damage to structures. It reflects the effect of surrounding environmental features such as buildings, trees, and vegetation on how wind flows over the terrain (FEMA, 2018). Denser obstructions tend to reduce wind speed at lower elevations, thereby affecting the wind pressure exerted on buildings. We assigned terrain IDs to each

building using geospatial data from the HAZUS repository. Each building's coordinates were used to extract the corresponding surface roughness value from census tract shapefiles covering the study area.

This building-specific hazard characterization represents a methodological advance over standard regional assessment tools such as FEMA's HAZUS-MH, which assigns a single representative wind speed to all buildings within a census tract based on a synthetic storm selection approach. HAZUS's tract-level approximation cannot account for the variation in wind exposure that exists within a tract due to differences in coastal proximity, terrain, and building location. Variation that standard tract-level approaches cannot capture and that may correlate with sociodemographic characteristics in ways relevant to environmental justice analysis. All wind hazard inputs in this study are assigned at the individual building level before aggregation to census tracts, providing a more accurate foundation for the sociodemographic analysis that follows.

3.2.3 Expected Annual Damage Calculation

After identifying the unique building ID and the corresponding wind speeds for different return periods, an extreme value distribution was set to the dataset. For our analysis, a Gumbel extreme value distribution was fitted as it is widely used for wind risk assessment (Eq. 1–3). The cumulative distribution function is given by:

$$F(v) = p(X < v) = \exp \left[-\exp \left(-\left(\frac{v - u}{a} \right) \right) \right]$$

1

where v is wind speed, u is the location parameter (intercept), and a is the scale parameter (slope). Solving for v gives:

$$v = u - a \ln [-\ln(p)]$$

2

where the annual non-exceedance probability p is related to the return period T by:

$$p = 1 - \frac{1}{T}$$

3

The Gumbel distribution was fitted for each building location, and the corresponding location and scale parameters for each building were identified. For each building, a Monte Carlo simulation of 50,000 iterations was performed. In each iteration, a random probability value was drawn from a uniform distribution between 0 and 1, and the corresponding wind speed was determined from Eq. 2. This process produced a building-specific distribution of wind speeds reflecting the full range of hazard intensities the structure is expected to experience over time, approximating the integral in Eq. 4.

$$EASD = \int_0^1 p(v) L(v) dv$$

4

For each simulated wind speed, the corresponding loss ratio was identified from the damage loss function database using the building's wBID and terrain ID. The database comprises 6,116 unique building attribute combinations, five terrain IDs, and nine damage loss description IDs, covering wind speeds from 50 to 250 mph.

Consistent with established catastrophe loss modeling frameworks (e.g., Hazus), expected annual damage includes direct economic losses associated with building damage, contents damage, and loss-of-use impacts. Accordingly, Expected Annual Structural Damage (EASD) was calculated by averaging loss ratios across all 50,000 iterations and combining building, contents, and loss-of-use components as follows:

$$EASD = EAD_B \times V_S + EAD_C \times 0.5 \times V_S + EAD_{Use} \times V_S \times \frac{1}{365 \times 7}$$

5

where V_S is the structural value of the building, EAD_B is the expected annual building damage ratio, EAD_C is the expected annual contents damage ratio (Consistent with standard practice in HAZUS-based loss estimation framework, contents value assumed to be 50% of structural value (FEMA, 2020), and EAD_{Use} is the expected annual loss-of-use ratio (converted to a dollar value by assuming monthly rent equivalent to 1/7 of structural value over 365 days (Amoroso & Fennell, 2008). Expected Annual Damage in Dollars (EADD) was calculated as the sum of dollar-denominated building, contents, and loss-of-use components. Building-level EASD and EADD estimates were then aggregated to the census tract level, retaining only residential structures, to produce the tract-level wind risk measures used in the sociodemographic analysis.

3.3 Sociodemographic Analysis Module

3.3.1 Data Sources and Analytic Sample

Data on all social and demographic variables, except for the proportion of rural residents in census tracts, were obtained from the 2018–2022 American Community Survey (ACS) five-year pooled estimates. Data on rural residence were obtained from the 2020 Decennial Census Demographic and Housing Characteristics (DHC) file. We confined the analysis to census tracts with a population of at least 100 to ensure validity of ACS estimates; two tracts with populations below 100 were excluded. In addition, data on median income was missing for one tract. The final analytic sample therefore included 708 tracts.

3.3.2 Wind Damage Outcome Variables

We examine how social and demographic attributes of census tracts are associated with eight wind risk outcomes assessed at the tract level: 1) *EASD_total* and its three subcomponents—expected annual damage ratios for building, contents, and use, and 2) *EADD_total* and its three subcomponents, expected annual damages in dollars for building, contents, and use. In the main analysis, we focus on *EASD_total* and *EADD_total*, while results for their six constituent measures are presented in the appendix (see Tables A2 and A3), as the findings for the two main measures largely hold for their respective components.

We derived per-structure estimates of all eight wind risk outcomes to avoid biases that could arise from correlations between the number of buildings and tract-level social and demographic characteristics (e.g., tracts with higher median income or more urban residents may also contain more buildings). Eq. 6 was used to calculate per-structure estimates of *EASD_total* (hereafter referred to as *EASD*) and its three constituent measures. Here, ratios were first multiplied by 100 to convert them to percentages before dividing by the number of buildings in each tract, to avoid extremely small values that could complicate interpretation. Per-structure values for *EADD_total* (hereafter referred to as *EADD*) and its three constituent measures were derived using Eq. 7, where values were directly divided by the number of buildings, as the values were sufficiently large. Finally, all eight outcomes were log-transformed to address positive skewness.

$$\text{Per structure value} = \frac{\text{Wind risk ratio} \times 100}{\text{Number of buildings in a tract}}$$

6

$$\text{Per structure value} = \frac{\text{Wind risk in dollars}}{\text{Number of buildings in a tract}}$$

7

3.3.3 Social and Demographic Independent Variables

Four categories of sociodemographic characteristics serve as focal predictors, selected based on prior environmental justice and disaster vulnerability research. First, racial composition is a core focus in environmental justice research, and more Black and Hispanic residents have been linked in studies to greater hurricane risks and impacts (Chakraborty et al. 2019; Logan et al. 2016; Smiley et al. 2022) at the same time that other research suggests an opposite relationship depending on the hazard and place under examination (e.g., Collins, Grineski, and Chakraborty 2018). Second, a local area's income has similarly mixed findings depending on the context: affluence can lead to greater risk as some coastal areas have high amenities and are therefore considered desirable by relatively well-off residents while other areas exhibit the opposite pattern (Collins, Grineski, and Chakraborty 2018; Logan et al. 2015; Tama et al. 2025). Third, housing make-up is an important component, as renters face particular vulnerabilities since rental housing is disproportionately older and of lower quality (Dundon et al., 2021) and structural improvements are not as incentivized for owners of rental properties (Lee and Van Zandt

2019; Peacock et al., 2007). Fourth, rurality is an important factor: while both urban and rural areas face considerable vulnerabilities, rural areas may face greater wind risk in particular because of aging housing stock and a higher prevalence of manufactured homes which are associated with greater structural vulnerability (García et al., 2023; Kapucu et al., 2013; Dhungana and Liu 2024). In all, understanding disparities in wind risk requires attentiveness to these socio-spatial factors.

All models presented include additional controls for important social and demographic correlates including the proportion of residents with a college degree or higher; residents employed in natural resources, construction, and maintenance occupations; median age; the proportion of non-citizens, and the share of seasonal, recreational, and occasional-use housing.

Prior to analysis, variables with extreme positive skewness were log transformed, with a small constant of 0.001 added to proportions before transformation to accommodate zero values. Transformed variables include proportion of other-race residents, proportion of Hispanic residents, proportion of noncitizens, proportion of rural residents, median income, and proportion of recreational housing.

3.3.4 Analytical strategy

Ordinary Least Squares (OLS) regression models were first estimated for all eight wind damage outcomes, including the full set of focal predictors and covariates. Because the analysis was conducted at the census tract level, model residuals were tested for spatial autocorrelation using Global Moran's I. In all eight models, results showed strong, statistically significant, and positive spatial autocorrelation among the residuals, violating the OLS assumption of independent errors and rendering OLS regression inappropriate. Lagrange Multiplier tests further indicated that spatial lag specifications were preferred over spatial error models across all outcomes (see Table A4). Accordingly, spatial lag models were estimated with the same set of predictors and covariates using a queen contiguity spatial weights matrix.

4. Results

4.1 Wind speed and surface roughness distribution across the study area

Figure 1 presents the modeled 700-year, 3-second peak gust wind speeds and surface roughness across southern Louisiana. These results provide the hazard context for interpreting subsequent damage and social vulnerability analyses. The results show the spatial variation in wind exposure, with the highest predicted gusts (150–170 mph) concentrated along the southeastern coastal areas. These coastal areas exhibit lower surface roughness, primarily due to the lack of obstructions such as trees and buildings, and the presence of open waterfronts. Inland parishes show more moderate wind speeds (115–140 mph), while western and central tracts, such as those in Cameron and Vermilion, experience lower exposures. Structures located in suburban, treed, or urban environments experience significantly reduced wind loads compared to those in open regions such as fields or waterfronts.

4.2 Expected Annual Structural Damage (EASD)

EASD is calculated as the sum of expected building, contents, and loss-of-use damage ratios normalized by structural value (Fig. 2). Results show that the higher loss ratio of structure is mostly situated in the closer areas of the coastline and southern parishes, including Terrebonne, Lafourche, Plaquemines, and portions of Iberia and St. Mary. Coastal buildings face higher wind speeds due to the lack of natural barriers (lower surface roughness), leading to significant structural damage and prolonged recovery periods. Conversely, urbanized or densely populated tracts (e.g., Baton Rouge, New Orleans) generally report lower EASD per structure.

4.3 Expected Annual Damage in Dollars (EADD)

The EADD distribution (Fig. 3) broadly mirrors EASD but diverges in revealing ways. The analysis shows a wide variation in structural damage losses, ranging up to approximately \$5M. Higher EADD zones, particularly in Jefferson, Orleans, Lafourche, and St. Charles, indicate greater financial exposure. Several rural tracts in Cameron and western Vermilion show high structural damage ratios (EASD) but relatively modest EADD, reflecting significant physical vulnerability without commensurately high property values. Conversely, tracts in coastal and near-coastal communities exhibit large EADD even where EASD is moderate, driven by the concentration of high-value housing stock.

4.4 Socio-economic disparities

4.4.1 Descriptive Analysis

Table 1 presents the descriptive statistics for all study variables across the 708 census tracts included in the analysis. The average EASD per structure was 0.332% of structural value (SD = 0.181), ranging from 0.084% to 1.353%, indicating substantial variation in structural wind risk across the study area. Average EADD per structure was \$718.50 (SD = \$497), with values ranging from \$125 to \$7,100, reflecting the additional influence of property values on dollar-denominated losses. On average, a tract had 31% non-Hispanic Black residents, 7% Hispanic residents, and 3% non-Hispanic, non-White residents of other races. The average proportion of rural residents in a tract was 19%, and, on average, 33% of residences were renter occupied indicating that the majority of residences were owner-occupied (67%). Median income across tracts averaged \$33,826, with values ranging from \$4,393 to \$83,523.

Table 1
Descriptive statistics

EASD	Mean	Standard deviation	Minimum	Maximum
	0.332	0.181	0.084	1.353
EADD	718.5	497	125	7100.3
Proportion of non-Hispanic Black residents	0.310	0.293	0	1
Proportion of Hispanic residents	0.070	0.074	0	0.532
Proportion of non-Hispanic residents of 'other' race	0.032	0.048	0	0.462
Proportion of rural residents	0.188	0.335	0	1
Median income	33826	11980	4393	83523
Proportion of renter -occupied housing	0.328	0.217	0	1
Proportion of noncitizens	0.030	0.043	0	0.275
Proportion of with a college degree or higher	0.279	0.183	0	0.909
Proportion of residents employed in NRCM	0.109	0.073	0	0.416
Median age	39.42	6.692	13.60	66
Proportion of recreational housing	0.028	0.066	0	0.690
Notes. N = 708				

4.4.2 Multivariate Regressions

Table A1 presents result from spatial lag regression models predicting EASD and EADD, respectively. In both models, the spatial autoregressive parameter (ρ) is statistically significant ($\rho = 0.905$ for EASD; $\rho = 0.774$ for EADD), indicating strong spatial dependence in wind damage outcomes, a tract's expected annual damage is partly determined by the damage levels of neighboring tracts. Because spatial lag coefficients cannot be interpreted like standard regression coefficients, we report direct, indirect, and total effects for all predictors (see Tables 2 and 3). Importantly, given the high value of ρ , the indirect (spillover) effects are mechanically large and dominated by the spatial weights structure rather than by any cross-tract causal process. The direct effects are the more interpretable quantity for understanding tract-level associations; the total and indirect effects should be read as reflecting the geographic clustering of both predictors and outcomes across the study area, not as evidence that conditions in one tract causally influence damage in adjacent tracts.

Table 2
Direct, indirect and total effects of the model predicting EASD

Variable	Direct	Indirect	Total
Proportion of non-Hispanic Black residents	0.037 (0.050)	0.234 (0.342)	0.271 (0.391)
Proportion of Hispanic residents	0.002 (0.009)	0.014 (0.063)	0.016 (0.072)
Proportion of non-Hispanic residents of 'other' race (log)	0.008 (0.007)	0.052 (0.048)	0.060 (0.055)
Proportion of rural residents (log)	0.020*** (0.005)	0.128** (0.041)	0.148** (0.045)
Median income (log)	0.082* (0.040)	0.524 [†] (0.295)	0.606 [†] (0.333)
Proportion of renter-occupied housing	0.243*** (0.068)	1.558** (0.535)	1.802** (0.594)
Proportion of noncitizens (log)	0.017* (0.008)	0.108 [†] (0.058)	0.125 [†] (0.066)
Proportion of with a college degree or higher (log)	-0.077 (0.082)	-0.494 (0.566)	-0.571 (0.646)
Proportion of residents employed in NRCM (log)	-0.012 (0.158)	-0.079 (1.068)	-0.092 (1.224)
Median age	0.002 (0.002)	0.016 (0.011)	0.018 (0.013)
Proportion of recreational housing (log)	0.011 [†] (0.006)	0.069 [†] (0.040)	0.080 [†] (0.045)
Notes. n = 708; standard errors in parentheses; [†] p<.10; * p<.05; **p<.01; ***p<.001			

Table 3
Direct, indirect and total effects of the model predicting EADD

Variable	Direct	Indirect	Total
Proportion of non-Hispanic Black residents	-0.020 (0.073)	-0.053 (0.202)	-0.073 (0.275)
Proportion of Hispanic residents	-0.005 (0.014)	-0.014 (0.038)	-0.019 (0.052)
Proportion of non-Hispanic residents of 'other' race (log)	0.037*** (0.010)	0.100** (0.032)	0.138*** (0.041)
Proportion of rural residents (log)	0.031*** (0.007)	0.084*** (0.023)	0.115*** (0.030)
Median income (log)	0.237*** (0.059)	0.634*** (0.186)	0.871*** (0.240)
Proportion of renter-occupied housing	0.723*** (0.099)	1.937*** (0.364)	2.661*** (0.439)
Proportion of noncitizens (log)	0.011 (0.012)	0.030 (0.033)	0.042 (0.045)
Proportion of with a college degree or higher (log)	0.153 (0.123)	0.411 (0.337)	0.565 (0.458)
Proportion of residents employed in NRCM (log)	0.009 (0.250)	0.023 (0.694)	0.032 (0.943)
Median age	0.004 [†] (0.002)	0.010 (0.007)	0.014 (0.009)
Proportion of recreational housing (log)	-0.002 (0.008)	-0.005 (0.022)	-0.007 (0.031)
Notes. n = 708; standard errors in parentheses; † p<.10; * p<.05; **p<.01; ***p<.001			

In the model predicting EASD, all focal predictors except racial composition variables were statistically significant. The proportion of rural residents showed a positive effect across direct (0.020), indirect (spillover; 0.128), and total effects (0.148). This finding shows that higher expected annual damage per structure within a tract is associated with a higher proportion of rural residents in that tract (direct

effect), and that this association is geographically clustered, with similar patterns appearing in neighboring tracts (indirect effect).

The direct, indirect, and total effects of the proportion of renter-occupied housing were positive and statistically significant. A one-percentage-point increase in the proportion of renter-occupied housing in a given tract was associated with a 0.24% increase in expected annual damage per structure in that tract (direct effect). The corresponding indirect effect was 1.56%, reflecting the strong spatial clustering of renter-dominated tracts and wind damage outcomes across the study area; this magnitude should be interpreted as evidence of geographic clustering rather than as a quantifiable cross-tract spillover process

In the model predicting EADD, the results for the proportion of rural residents, median income, and the proportion of owner-occupied housing were similar to those in the model predicting EASD. In addition, for racial composition, the proportion of residents of “other” races emerged as statistically significant, with direct, indirect, and total effects all statistically significant. A 1% increase in the proportion of residents of “other” races in a given tract was associated with an estimated 0.04% increase in expected annual damage per structure in that tract and a 0.1% increase in neighboring tracts. As in the previous model, the indirect spillover effects of all focal predictors were larger than the direct effects.

For the control variables, the proportion of non-citizens was positively and significantly associated with EASD. The direct effect was statistically significant, while the indirect and total effects were only marginally significant. In contrast, no statistically significant association was found with EADD. The proportion of seasonal, recreational, and occasional-use housing was also positively and marginally associated with EASD, but it was not significant in the model predicting EADD.

For all three statistically significant predictors, indirect spillover effects were larger than direct effects, consistent with the strong spatial dependence in wind damage outcomes across neighboring census tracts. While this pattern suggests that wind vulnerability is geographically clustered, it should be interpreted with caution, as the magnitude of indirect effects is influenced by the high spatial autoregressive parameter in the model. Nonetheless, the results indicate that wind risk is not isolated to individual tracts but exhibits broader spatial continuity across the study area.

To ensure that the observed associations are not merely driven by broader cross-metropolitan differences in sociodemographic composition, we conducted a supplementary analysis using group-mean centered predictors within Core Based Statistical Areas (CBSAs), which uniquely identify the metropolitan or micropolitan area to which each tract belongs. Group mean centering was computed by subtracting each tract’s value of a variable from the mean tract value in that CBSA. Results using the group mean centered predictors were substantively similar to the original models: the proportion of rural residents, the proportion of renter-occupied housing, and median income remained statistically significant and positively associated with both EASD and EADD. These findings suggest that the observed relationships are not solely attributable to between-CBSA differences but also reflect inequalities within metropolitan and micropolitan areas (see Table A5).

Figures 4 and 5 display predicted values of EASD and EADD, respectively, across the 5th, 25th, 50th, 75th, and 95th percentiles of each significant predictor (i.e., the proportion of rural residents, the proportion of renter occupied housing and median income), holding all other variables at their mean. Each of these variables contribute independently and additively to wind damage risk rather than through synergistic combinations in moderating, or interaction, effects.¹ These visualizations complement the regression tables by illustrating the practical magnitude and shape of each association.

For rural concentration, predicted EASD and EADD remain stable at 0.026 and \$271, respectively, from the 5th through the 50th percentile. Beyond the 50th percentile, however, predicted EASD and EADD increase sharply. For example, predicted EASD increases from 0.057 to 0.067, a 17.5% increase, between the 75th (19.8%) and 95th (100%) percentiles of rural residents. Predicted EADD increases from \$331 to \$350 between the same percentile range, albeit marking only a 5.7% increase, notably smaller than the increase observed for EASD.

For the proportion of renters, both predicted EASD and EADD increase quite steadily across the examined percentiles. Predicted EASD rises from 0.024 to approximately 0.036 between the 5th (4.7%) and 50th (28%) percentiles, representing a 50% increase, and further increases to approximately 0.060 by the 95th (71%) percentile, an additional 67% increase. Predicted EADD follows a similar pattern, increasing from about \$138 to \$269 between the 5th and 50th percentiles (a 95% increase), and then rising further to \$512 by the 95th percentile, representing an additional 90% increase.

For median income, predicted values show a positive gradient across percentiles for both outcomes (Figs. 4c and 5c). The association is present but modest for EASD, consistent with income's marginal total effect ($p < 0.10$), while the EADD gradient reflects a substantially more reliable association ($p < 0.001$), consistent with asset value concentration as the primary mechanism. This pattern is evident in the increasing predicted values across the income distribution. Predicted EASD rises from 0.026 to 0.039 between the 5th (\$18,253) and 50th (\$31,457) percentiles (a 50% increase) and further increases to 0.052 by the 95th (\$56,877) percentile (an additional 33% increase). Predicted EADD follows a similar but relatively stronger pattern, increasing from \$194 to \$294 between the 5th and 50th percentiles (a 52% increase) and rising further to \$402 by the 95th percentile (an additional 37% increase).

Figure 6 presents bivariate maps illustrating the geographic concentration of the two vulnerability patterns identified in the regression analysis. The bivariate map of EASD and the proportion of rural residents shows that census tracts with both high EASD and moderate to high rural concentration are found across nearly all shoreline parishes, as well as in several inland parishes including St. James, Assumption, and Iberia. Farther inland, however, census tracts in areas such as St. Tammany and Livingston predominantly exhibit low EASD regardless of their rural concentration, indicating that the structural vulnerability patterns is most pronounced in coastal and near-coastal rural communities.

The bivariate map of EADD and median income shows that census tracts characterized by both high EADD and moderate to high median income are primarily concentrated along Louisiana's coastal parishes, including Cameron, St. Mary, Vermilion, Terrebonne, Jefferson, and St. Bernard. A small number

of inland tracts particularly in St. John the Baptist, Ascension, St. James, Orleans, and Calcasieu, also exhibit this combination. By contrast, most inland census tracts in areas such as Livingston, St. Tammany, St. Martin, and Tangipahoa display either moderate to high income with low EADD, or low income with low EADD.

5. Discussion and Conclusion

5.1 Two Distinct Dimensions of Wind Vulnerability

This study shows that the link between community characteristics and wind damage risk in coastal Louisiana depends strongly on how damage is defined and measured. By analyzing both EASD, which reflects proportional physical damage, and EADD, which reflects economic loss, the results reveal that these two measures capture distinct dimensions of vulnerability. While these patterns are consistent with differences in housing quality and asset concentration, the analysis does not directly test these mechanisms.

Using spatial lag regression models based on building-level probabilistic wind damage estimates across 708 census tracts, the analysis indicates that rural residence and renter occupancy are consistently associated with both outcomes. Their statistical significance across models suggests that these factors may be linked to not only spatial vulnerability from the hazard (i.e., proximity to the coast), but also underlying structural vulnerabilities, potentially reflecting differences in housing characteristics such as building age, construction type, maintenance, and code compliance that are not directly observed in the data which may contribute to both higher physical damage and greater monetary loss.

In contrast, median income is associated with EADD strongly and consistently ($p < 0.001$), but its association with EASD is modest with statistically significant direct effects ($p < 0.05$) but only marginally significant indirect and total effects ($p < 0.10$). The stronger and more consistent association for median income is with dollar losses rather than structural damage ratios, a pattern more consistent with asset value concentration than with structural fragility.

The bivariate map of EADD and median income adds an important layer to this interpretation. At first glance, it may seem inconsistent, as many high-EADD tracts in western coastal parishes such as Cameron and Vermilion are associated with lower, rather than higher, incomes. However, these areas are also among the most rural in the study region. In these cases, high EADD appears to be driven by structural vulnerability which is greater physical damage occurring in lower-value housing located in highly exposed coastal environments. The regression results help clarify this pattern. By accounting for rural concentration, renter occupancy, and income at the same time, the model isolates the independent role of each factor. This means that the positive relationship between income and EADD reflects something beyond rural exposure alone. Specifically, the concentration of higher-value homes in coastal and suburban parishes such as Jefferson and St. Charles, where losses are amplified by property values.

Taken together, the maps and regression tell a consistent story: both dimensions are present on the ground, but the regression helps disentangle them analytically.

For racial composition, the analysis finds no statistically significant associations between either wind damage metric and the proportions of non-Hispanic Black or Hispanic residents, although proportion of “other” race is statistically significant for EADD but not EASD. This contrasts with patterns commonly observed in flood-focused environmental justice research (e.g., Smiley et al. 2022; Flores et al. 2025) and suggests that wind vulnerability in coastal Louisiana may not align with the same racialized exposure dynamics documented for other hazards.

5.2 The Structural Vulnerability Pattern: Rural Communities and Renters

The results point to two distinct but complementary dimensions of wind vulnerability in coastal Louisiana, reflecting differences between structural fragility and economic exposure. Rural residence and renter occupancy emerge as the only predictors consistently associated with both proportional structural damage and dollar-denominated losses, a pattern consistent with underlying vulnerabilities associated with housing performance and proximity to the coast rather than variations in property value alone. Because EASD represents damage relative to structural value, the observed associations are consistent that rural and renter-dominated communities experience genuinely higher physical wind damage rather than damage that simply reflects higher residential property values. Moreover, as illustrated by the bivariate maps, the higher levels of physical wind damage observed in renter-concentrated and predominantly rural tracts are not solely driven by their proximity to the coast. Census tracts with moderate to high proportions of renters or rural residents and high damage are not necessarily concentrated along the coastline, suggesting that factors beyond coastal location including housing stock characteristics may contribute to elevated damage in these communities.

Prior research suggests that residents in rental housing and rural communities tend to be more vulnerable to disaster impacts, partly because they are more likely to reside in less resilient housing structures that do not comply with current building codes. In rural areas, aging housing stock and manufactured homes, both more prone to destruction during disasters, are key features of structural vulnerability (García et al., 2023; Kapucu et al., 2013; Dhungana and Liu 2024). Rental housing similarly tends to be older and of lower quality (Dundon et al., 2021). In addition, renters generally lack authority to implement structural improvements, while landlords often face limited incentives to invest in resilience measures that may not translate into higher rental returns (Lee and Van Zandt 2019). Post-disaster recovery and rebuilding may also be slower for rental properties, as owners, whether individual or commercial, bear responsibility for repairs and may delay reconstruction due to financial constraints, leaving tenants structurally vulnerable for extended periods (Peacock, Dash, and Zhang 2007). These patterns are consistent with the possibility that structures in predominantly rural tracts and in rental housing—dominant tracts more likely to lack critical protective measures such as robust roof-to-wall connections, adequate roof deck attachment, secondary water resistance, and effective opening

protection. The building-level probabilistic modeling framework used in this study is particularly sensitive to such variations, consistent to the interpretation that these communities face systematic structural disadvantages.

Structural fragility in these communities is further compounded by broader social and geographic factors that shape disaster impacts and recovery capacity. Rural communities also tend to receive less attention in disaster recovery efforts, are geographically isolated in terms of transportation and communication networks, and face place-based vulnerabilities such as food insecurity and limited healthcare access (Bailey et al., 2014; Coughlin et al. 2019; Drakes et al. 2021), all of which amplify their vulnerability to hurricane impacts. Similarly, renters face parallel recovery challenges, including reduced eligibility for certain forms of post-disaster assistance, lack of access to flood insurance, and increased risk of permanent displacement following severe housing damage (Dundon et al., 2021). These patterns highlight a structural vulnerability pathway in which physical housing performance and spatial proximity to the coast interact with social conditions to produce compounded inequities in wind hazard outcomes.

5.3 The Economic Exposure Pattern: Asset Value Concentration and Dollar Losses

Median income shows a strong and statistically significant association with EADD across direct, indirect, and total effects, while its relationship with EASD is comparatively modest. The bivariate map (Fig. 6) reveals that this relationship is not spatially uniform. Coastal suburban parishes such as Jefferson and St. Charles display a combination of high EADD and moderate to high median income consistent with an asset-concentration interpretation, while several western coastal parishes including Cameron and Vermilion show high EADD alongside lower incomes, a pattern more consistent with the structural vulnerability dimension discussed in Section 5.2.

These lower-income, high-EADD tracts are also among the most rural in the study area, and their elevated economic losses are more consistent with the structural vulnerability pathway rather than asset value concentration. The multivariate regression accounts for this by controlling simultaneously for rural concentration, identifying an income-EADD association that remains after rural concentration is accounted for, although unmeasured confounders may still influence this association.

This pattern is consistent with coastal amenity dynamics, whereby higher-income households are drawn to coastal locations offering recreational, aesthetic, and lifestyle benefits despite elevated hazard exposure (Cutter and Emrich, 2006). As Cutter and Emrich (2006) note, the wealth gap between the richest and poorest Americans is “especially evident in coastal counties, where the rich live right along the shore, and the income gradient decreases with distance away from the water’s edge” (p. 103). In coastal Louisiana, the regression and bivariate map results are consistent with this dynamic: economic wind losses are concentrated in parishes that combine high property values with substantial modeled wind intensities, although our analysis does not directly measure coastal proximity or distinguish amenity-driven location choices from other factors that link income and coastal location.

The proportion of non-Hispanic residents of “other” races shows no significant association with EASD but is strongly and positively associated with EADD. As this category corresponds to a wide diversity of residents (e.g., Vietnamese American residents in urban and rural contexts, East Asian American or South Asian American residents in suburban parishes, and indigenous groups in rural areas, among others), future research would be needed to understand what is driving this relationship, although our findings point here to disproportionate risk faced by census tracts with more residents of these groups.

These findings suggest that wind vulnerability in coastal Louisiana is associated with two distinct sociodemographic patterns: one consistent with the intersection of socioeconomic marginalization, physical structural fragility, and locational proximity to the coast, and another associated with the spatial distribution of property value that may shape economic exposure. These patterns affect different populations and emerge through different processes, underscoring that wind-related inequality cannot be understood through a single dimension of risk. Recognizing the coexistence of these mechanisms provides a more nuanced understanding of vulnerability and highlights the importance of measurement choice in shaping interpretations of environmental risk.

5.4 Policy implications: a two-track approach to wind risk mitigation

The identification of two distinct vulnerability patterns suggests that wind risk mitigation cannot rely on a single policy strategy. Interventions that address structural fragility will not resolve the concentration of high-value assets in exposed coastal areas, and approaches focused solely on socioeconomic disadvantage may overlook important drivers of wind risk.

Assuming the structural vulnerability pattern reflects housing quality differences as suggested above, the primary leverage points involve housing quality and tenure dynamics. Strengthening building code enforcement and expanding retrofit programs remain central tools, but their effectiveness depends on reaching the building stock most at risk particularly in highly rural communities and renter-dominated housing markets. Programs such as Louisiana’s FORTIFIED Home initiative provide a model for improving wind resistance, yet participation in rural and rental contexts is often constrained by cost and by misaligned incentives between landlords and tenants. Policies that directly address this mismatch, including landlord-focused tax incentives, conditional retrofit requirements tied to rental licensing, and expanded mitigation grant access for manufactured and mobile homes, may be better positioned to reduce structural vulnerability than homeowner-centered voluntary programs.

The economic exposure pattern calls for a fundamentally different policy response — one focused on managing where high-value development occurs rather than on structural retrofits. Because economic wind exposure in high-income tracts tend to be driven primarily by asset concentration in coastal locations, the appropriate leverage point is land use planning that moderates further intensification in the highest-exposure zones. Zoning policies that restrict new high-density residential development in areas with documented wind exposure exceeding defined thresholds, combined with incentives for strategic

landward relocation of the most exposed structures over time, address the underlying location problem rather than its financial consequences.

Nature-based solutions offer a complementary approach with particular relevance to coastal Louisiana. Coastal wetlands, barrier marshes, and vegetative buffers attenuate wind energy and reduce storm intensity before it reaches developed areas. Louisiana's ongoing wetland loss driven by subsidence, sea level rise, and channelization has progressively removed natural protection from coastal communities, amplifying wind exposure for both high-value coastal developments and structurally vulnerable rural communities further inland. Investments in wetland restoration and living shoreline programs through the Louisiana Coastal Master Plan therefore represent dual-benefit interventions: they reduce physical wind exposure for structurally vulnerable communities while simultaneously limiting the economic loss concentration that characterizes the coastal sorting pathway. From an environmental justice standpoint, nature-based coastal protection is among the few policy instruments capable of addressing both dimensions simultaneously.

Finally, the strong spatial clustering of wind damage outcomes observed in the analysis indicates that wind vulnerability is regional in character. Although the indirect effects from the spatial lag models do not provide direct evidence of cross-tract causal spillover, the geographic clustering of structurally vulnerable communities and economically exposed areas implies that mitigation planning confined to individual census tracts or municipalities may be insufficient. Parish-level or multi-parish coordination, including regional building stock assessments, shared enforcement capacity, and collaborative retrofit program delivery, may better align mitigation strategies with the geographic scale at which wind vulnerability is concentrated.

6. Limitation and Future Research

Several limitations of this study warrant acknowledgment. First, the EASD and EADD estimates produced by the building-level pipeline are not directly validated against observed loss datasets. The fragility functions underlying the estimates are derived from the Hazus framework, which has been calibrated at regional scales. As a result, the absolute magnitudes of tract-level losses should be interpreted as model-based estimates rather than precise predictions of realized damage. The primary strength of the analysis lies in identifying relative spatial and sociodemographic patterns of expected wind damage. External validation using observed loss data represents an important direction for future research.

Second, the analysis lacks direct, tract-level measures of housing quality and structural characteristics such as building age, construction type, manufactured home prevalence, and code compliance. While the building-level wind modeling framework captures structural variation through Monte Carlo assignment of secondary attributes drawn from regional Hazus distributions, these probabilistically assigned attributes are not linked back to the sociodemographic predictors in the regression models. As a result, the interpretation that rural residence and renter occupancy reflects underlying structural fragility is inferred from the joint pattern of associations with EASD and EADD and from prior literature,

rather than directly demonstrated. Other plausible contributors, including unmeasured locational exposure, sheltering effects, microclimate variation, and differences in pre-storm mitigation behavior, cannot be ruled out. The structural vulnerability pattern reported in this study should therefore be interpreted as a hypothesis consistent with the data rather than a directly tested causal pathway. Future research integrating ACS housing-age and mobile home data, parcel-level construction records, or post-disaster damage assessments with sociodemographic variables would provide a more rigorous test of this interpretation.

Third, because analysis is conducted at the census tract level, within-tract variation in both housing characteristics and household socioeconomic conditions is necessarily obscured. Lower-income residents and higher-income residents within the same tract face different actual exposures that tract-level averages cannot capture.

Fourth, the study focuses on a single hazard in a single state. Louisiana's specific coastal geography, land use history, and insurance market context may limit the generalizability of findings, particularly the coastal amenity sorting dynamic, to other regions. Additionally, coastal Louisiana communities face simultaneous flood and wind exposure, and the interaction between these hazards is not addressed here.

Future research should integrate detailed building inventory data with socioeconomic characteristics at finer spatial scales to more directly examine the links between housing quality, structural performance, and social vulnerability. Longitudinal designs tracking vulnerability before and after hurricane events would strengthen the interpretability of the proposed mechanisms. Comparative studies extending this framework to other coastal regions would test whether the two-pathway structure identified here generalizes beyond Louisiana, and integrated flood-wind analyses would address the compound hazard dynamics that single-hazard studies necessarily omit.

Declarations

Conflict of Interest statements

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contributions

Ayat Al Assi: Conceptualization, Methodology, Formal analysis, Investigation, Writing (original draft), Writing (review and editing), Visualization. **Fuad Hasan:** Data curation, Investigation, Resources, Writing (review and editing). **Kevin T. Smiley:** Conceptualization, Methodology, Formal analysis, Writing (original draft), Writing (review and editing). **Naduni Jayasinghe:** Methodology, Formal analysis, Writing (original

draft), Writing (review and editing). **Rubayet Bin Mostafiz**: Visualization, Writing (review and editing). **Md Adilur Rahim**: Data curation, Resources, Writing (review and editing). **Carol Friedland**: Supervision, Writing (review and editing).

8. Data Availability

The National Structure Inventory data used to construct the building inventory are publicly available from the U.S. Army Corps of Engineers. Wind hazard rasters were obtained from the ASCE under a data use agreement and cannot be redistributed by the authors. American Community Survey and Decennial Census data are publicly available from the U.S. Census Bureau. Tract-level EASD and EADD estimates produced by the building-level damage pipeline, along with the regression analysis code, are available from the corresponding author on reasonable request.

Funding Acknowledgement

This study was supported by the U.S. Department of the Treasury through the Louisiana Coastal Protection and Restoration Authority's Center of Excellence Research Grants Program under the Resources and Ecosystems Sustainability, Tourist Opportunities, and Revised Economies of the Gulf Coast States Act of 2012 (RESTORE Act) (Award No. RCEGR260007-01-01). The statement, findings, conclusions, and recommendations are those of the authors and do not necessarily reflect the views of the Department of Treasury

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Footnotes

1. To assess whether the three significant focal predictors operate independently or in combination, we estimated eight additional spatial lag models testing all two-way and three-way interaction terms among rural proportion, renter concentration, and median income. The three-way interaction and both income-related two-way interactions (income × rural; income × renters) were non-significant for both EASD and EADD. The only significant interaction was between rural proportion and renter concentration, which was marginally significant for EASD ($p < 0.10$) and significant for EADD ($p < 0.05$), indicating a modest attenuation of the rural effect at higher renter concentrations. Because this interaction was marginal for EASD and its substantive interpretation does not alter the main findings, the primary analysis focuses on main effects. Full interaction model results are available from the authors upon request.

Figures

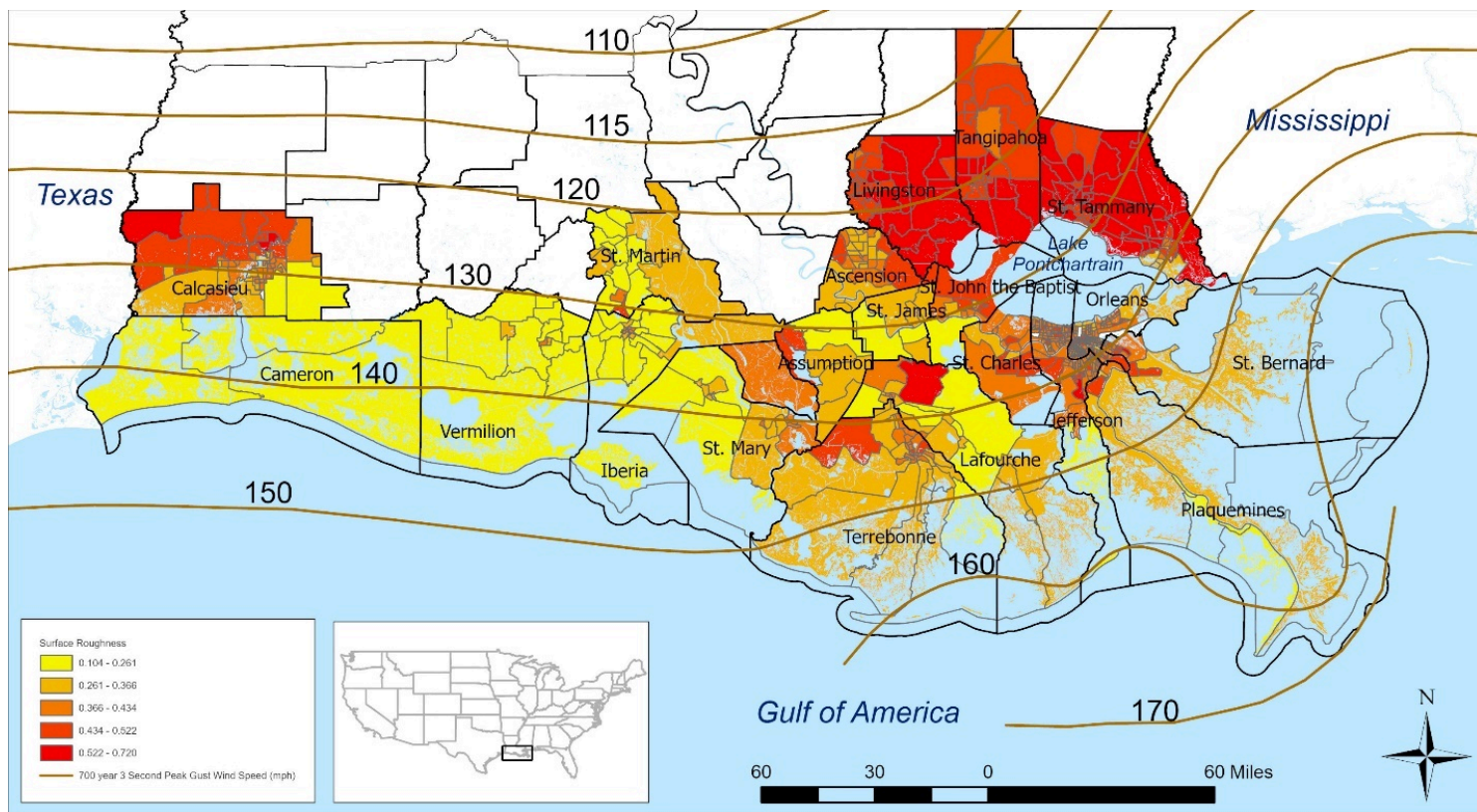


Figure 1

Surface roughness and wind speed contour within the study area

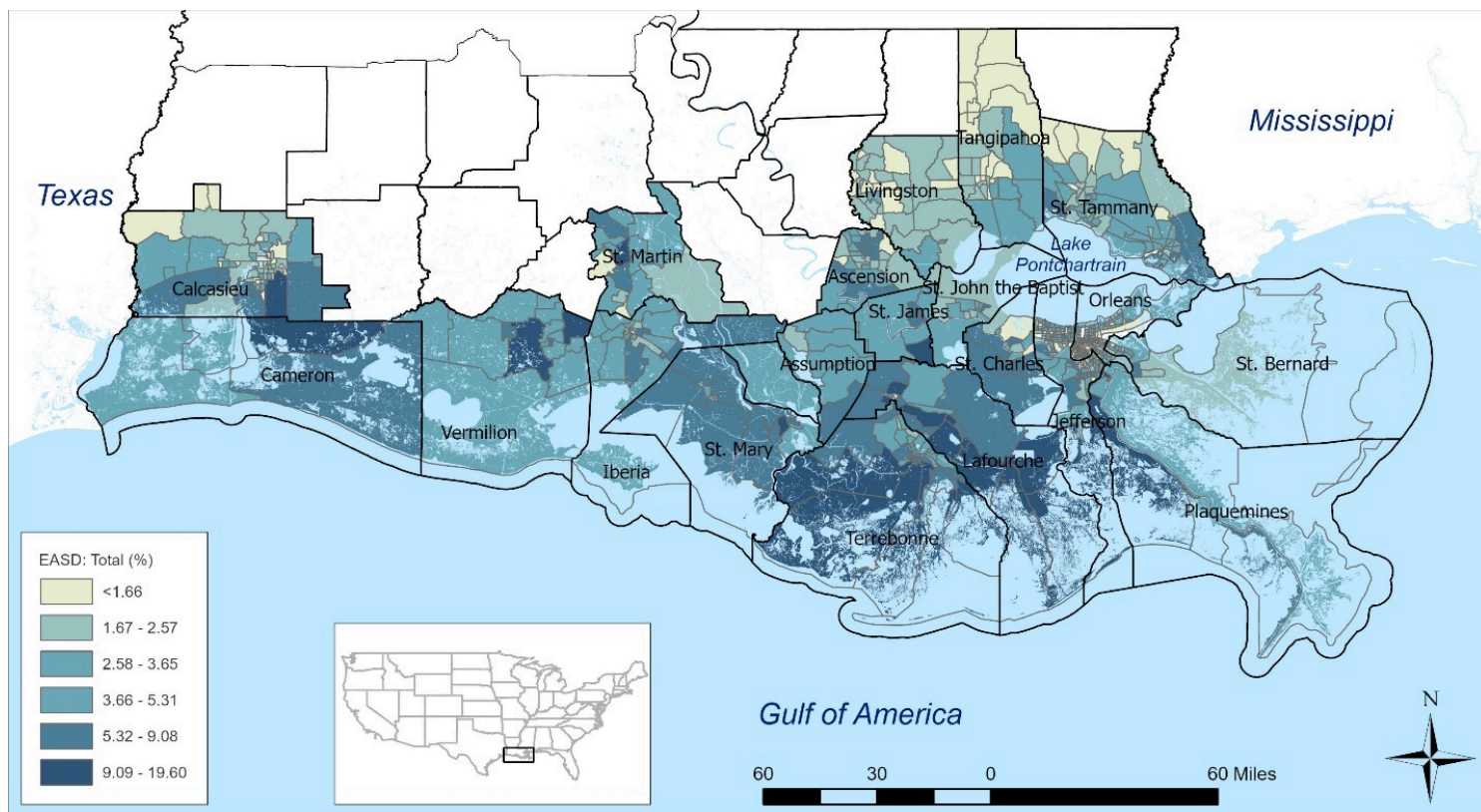


Figure 2

Total Expected Annual Structural Damage (EASD_{Total})

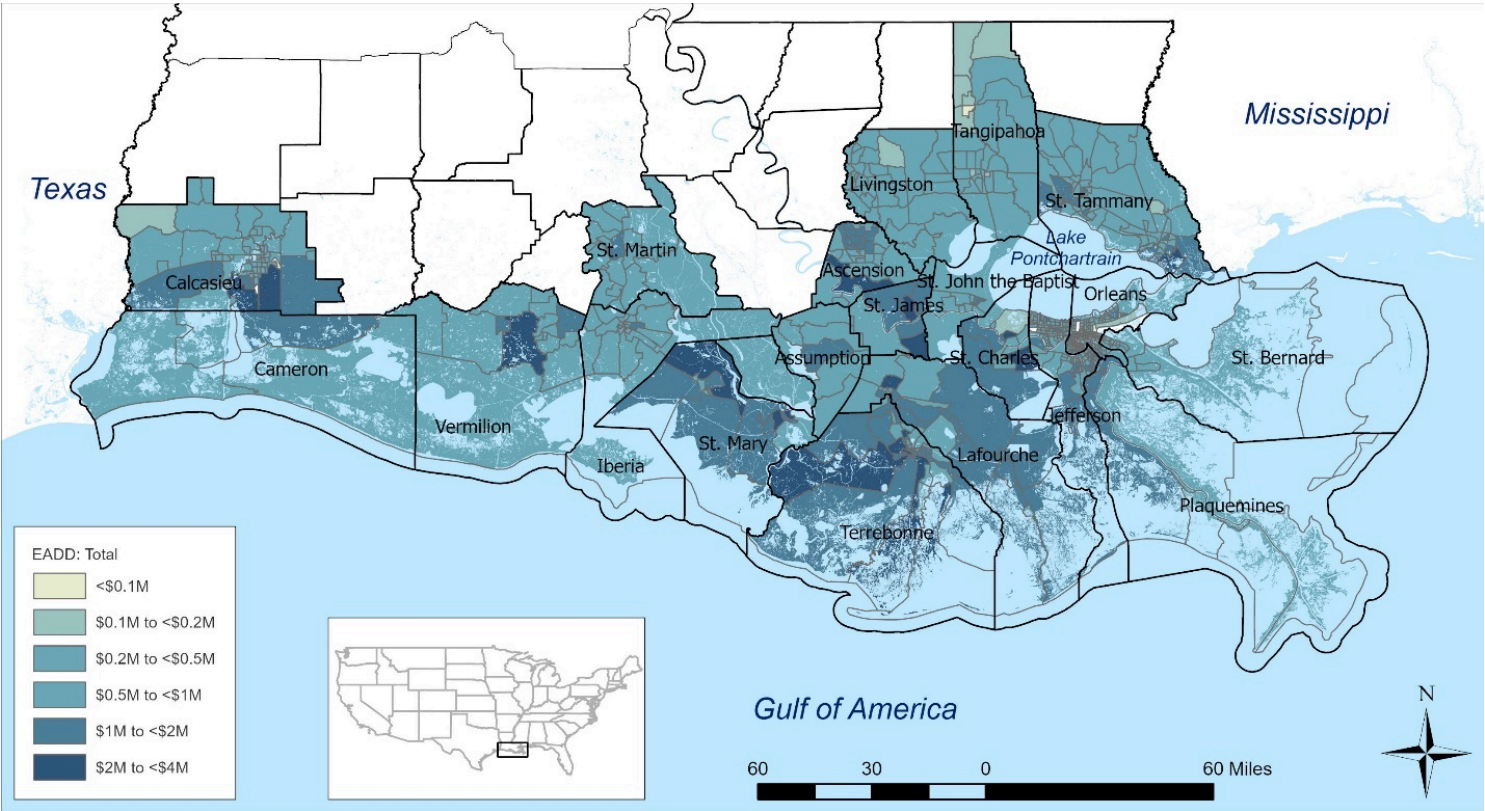


Figure 3

Total Expected Annual Damage in Dollar (EADD_{Total})

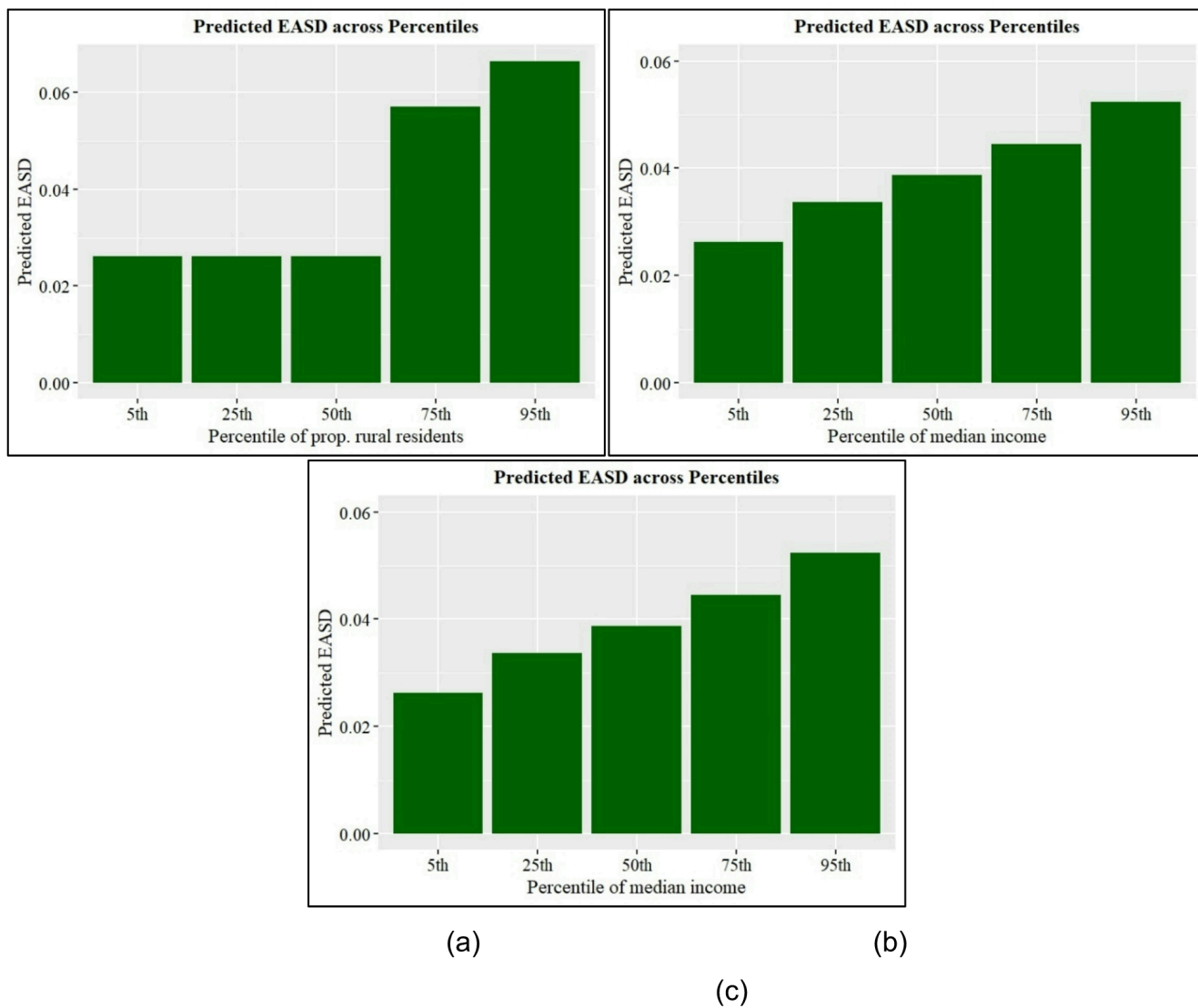


Figure 4

Predicted EASD across percentiles of significant sociodemographic predictors

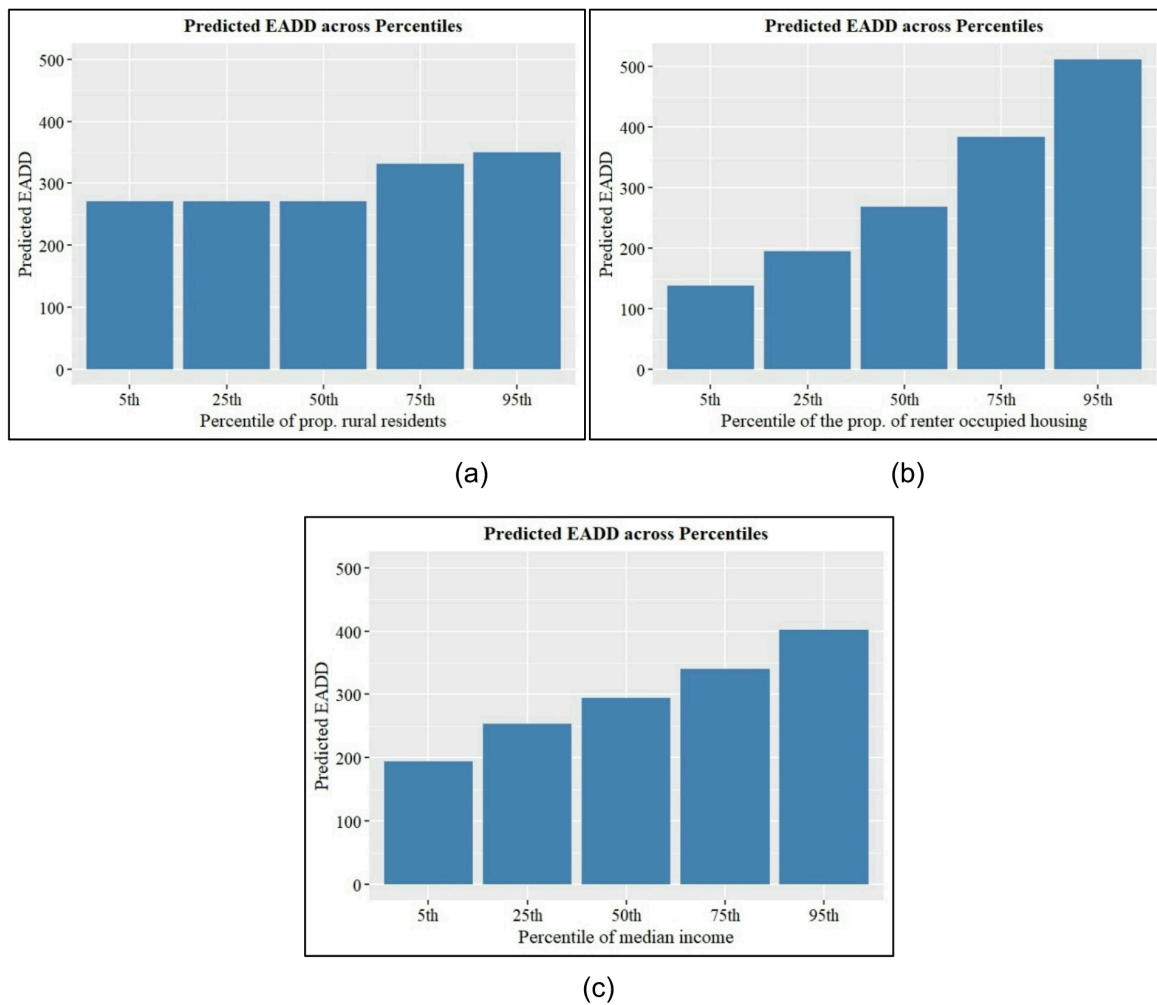


Figure 5

Predicted EADD across percentiles of significant sociodemographic predictors

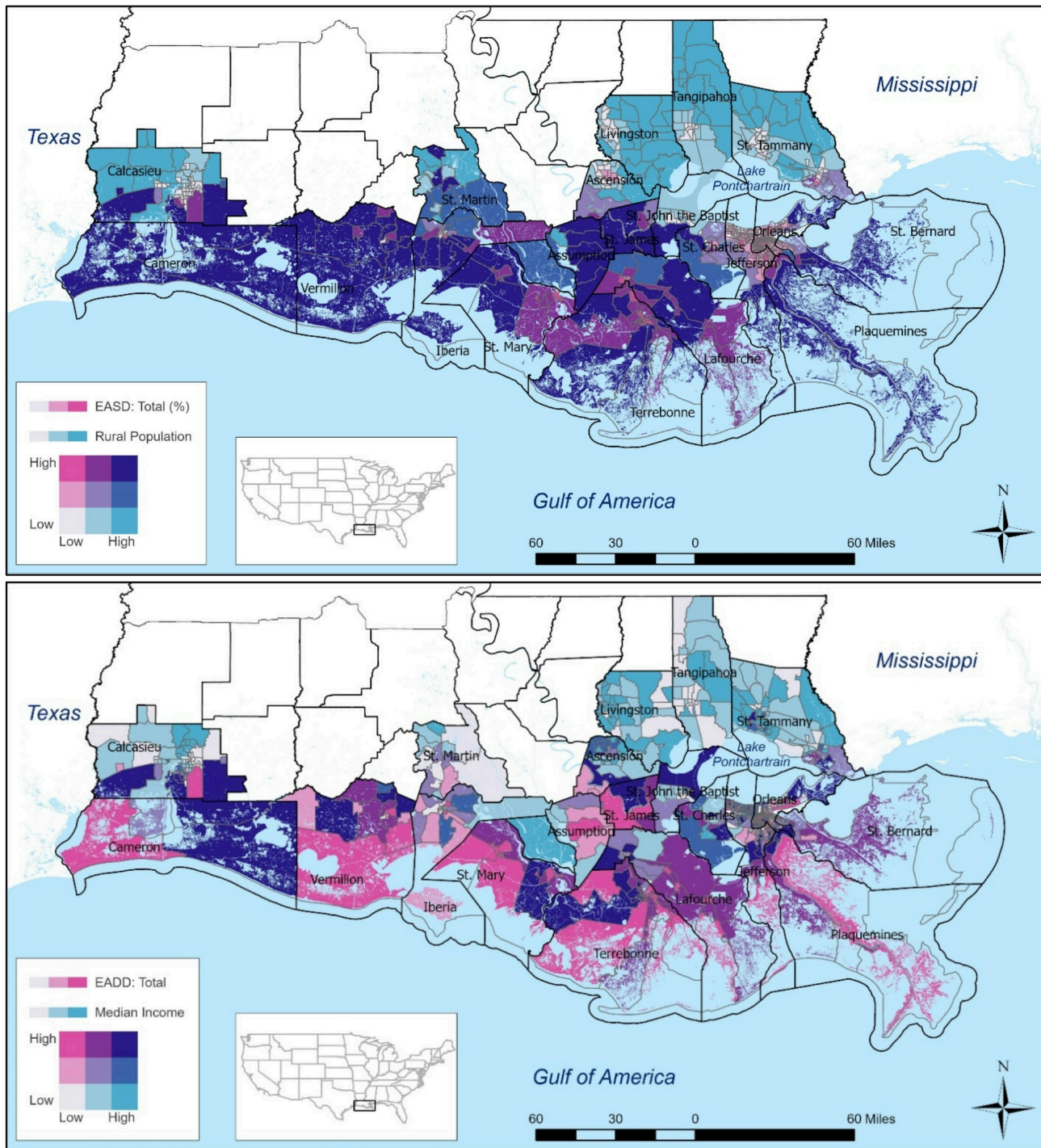


Figure 6

Bivariate maps of EASD and proportion of rural residents and EADD and median income

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryMaterials.docx](#)