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Insurance Coverage and Flood Exposure in the Gulf of Mexico: Scale, Social Vulnerability, Urban Form, and Risk Measures

Anissa Hyde [1,2], Robert Habans [2,3], Mariam Valladares-Castellanos [1,4] and Thomas Douthat [1,4,*]

1 Department of Environmental Sciences, College of the Coast and Environment, Louisiana State University, Baton Rouge, LA 70802, USA; mvalla3@lsu.edu (M.V.-C.)
2 The Data Center, New Orleans, LA 70163, USA; robert.habans@louisiana.edu
3 Blanco Center for Public Policy, University of Louisiana Lafayette, Lafayette, LA 70503, USA
4 LA-SEER Center, Baton Rouge, LA 70802, USA
* Correspondence: tdouthat1@lsu.edu; Tel.: +1-225-578-8810

Abstract: Increasing flood losses in the Gulf of Mexico related to development patterns and climate hazards pose serious threats to resilience and insurability. The purpose of this study is to understand how scale, social vulnerability, risk, and urban form relate to National Flood Insurance Program (NFIP) policy coverage and flood exposure. Our multilevel models identify that flooding is significantly clustered by region and counties, especially shoreline counties. Our measures of risk suggest that the Federal Emergency Management Agency (FEMA) special flood hazard area (SFHA) underestimates risk and exposure when compared with the Flood Factor and that there is some compensation in terms of insurance coverage, suggesting a pattern of adverse selection. Older housing stock appears both less insured and less exposed, raising questions of whether current growth patterns are increasing risk independent of environmental change. Our models suggest that census tracts with higher percentages of black residents are less insured and more exposed, and a similar pattern exists for rural areas. Our results highlight the need to seek common solutions across the Gulf of Mexico, concentrating on the most flood-exposed counties, and that specific resilience strategies may be necessary to protect areas with socially vulnerable populations, especially in rural areas. Underlying challenges exist due to the spatial relationship between exposure and social vulnerability and the potential for adverse selection in insurance markets due to different measures of risk.

Keywords: National Flood Insurance; flooding; social vulnerability; natural hazards; climate risk; SFHA; Gulf of Mexico

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1. Introduction

Flooding continues to strain the economy, infrastructure, and people of the Gulf of Mexico region. Flood risk may be increasing disproportionately among vulnerable groups across the United States, particularly in the Southeast region [1]. Environmental inequalities are shown through natural and industrial hazards, including proximity to flood zones and infrastructure [2–4]. Additionally, states on the Gulf Coast are experiencing insurance affordability crises, but these have uneven impacts by state and metro area [5–8]. This study uses National Flood Insurance Program (NFIP) data to construct an NFIP insurance coverage index and flood exposure (NFIP claims). We explore how the distribution of flood exposure and NFIP uptake correlates with measures of social vulnerability, urban form, and flood risk in the Gulf of Mexico region.

The current study aims to fill the gap between previous findings focusing on exposure to flooding, which often lack significant geographical breadth or spatial granularity, and those based on risk estimates, which use models that may not reflect actual exposure patterns. We respond to calls for greater empirical examination of local and regional level variation in climate hazards and resilience in terms of insurance and exposure [9]. Additionally, we examine the link between exposure and potential insurance gaps for vulnerable groups. Our study captures neighborhood-level exposure and insurance exposure by analyzing longitudinal insurance claims data on flood exposure across the Gulf Coast region in two periods (2010–2014, 2015–2019), which allows for examining patterns, scales, and potential disparities in exposure to flood damage and protection via NFIP insurance. We make novel use of NFIP data to strengthen our ability to identify if disparities in exposure and flood insurance exist in the Gulf Coast. This is of particular interest given the challenges climatic hazards are presenting to insurance markets and estimates in the National Climate Assessment that coastal areas will experience greater flood hazards in the future.

Our study first builds an NFIP Coverage Index model and then uses it to estimate a coverage-normalized exposure model based on NFIP claims. In doing this, we aim to model and compare the scalar element of flood hazard exposure and insurance coverage around the Gulf Coast, where there are questions about exposure and vulnerability at the regional (commuting zone), county, and neighborhood scale. We address questions of social vulnerability, given that previous studies have highlighted potential disparities for low-income and historically marginalized communities. The study also uses exposure patterns to examine measures of risk and "risk difference" in terms of how traditional measures of flood risk (Special Flood Hazard Areas) may underestimate property level risk. Finally, we control for coastal status, housing characteristics, and urban form.

1.1. Background on Risk and Exposure to Flooding

Exposure to natural hazards is typically measured in multiple ways. One way is through localized or single-event studies, which have fixed spatial and temporal scopes that might homogenize localized patterns over time and space [3,10–12]. Another common approach is to measure exposure using modeled risk predictions based on Federal Emergency Management Agency (FEMA) 100-year floodplains special flood hazard area (SFHA) or First Street Foundation Data (FSF) [13]. Other studies of insurance are often based on modeled or national individual policy data [6,14] and infrequently include neighborhood-level social and environmental controls.

In this study, we used NFIP claims as a response variable and addressed insurance coverage, especially since NFIP is noted for its low and variable rates of participation. The NFIP has provided residential flood insurance for the United States since 1968, but increasingly expensive southeastern disasters like Hurricane Andrew (1992), Katrina (2005), Ike (2008), Harvey (2017), and Ida (2021) have kept the federal program in a concerning amount of debt. The program's resources have been strained due to more frequent and intense flooding events and escalating costs, thus exposing its limitations [5,7,8,15]. This crisis jeopardizes the affordability and availability of flood insurance, placing communities and policyholders at increased risk. Studies of coverage and claims have tended to focus on characteristics of the structure and area and not their social correlates [6]. Our study provides a novel approach to modeling tract-level determinants of coverage, risk, and exposure in an analogous way compared to the studies cited above.

1.1.1. Risk and Difference in Risk Measures ("Risk Difference")

In the US, flood risk is often described around a regulatory floodplain [16]. This approach identifies high flood-risk areas as having an estimated 1 percent chance of flooding each year, according to FEMA. These Special Flood Hazard Areas (SFHAs) are divided into zones A and V, the latter being coastal areas subject to wave action (storm surge). Flood heights are also more likely to reach a certain level above the base flood elevation as defined by FEMA in SFHAs than in lower-risk zones, which include the 500-year floodplain [6]. Some criticize these measures, both technically, due to their update process and their binary approach [17]. Other measures have arisen and gained prominence in the literature, such as the First Street Foundation (FSF) Risk Factor, which provides parcel-level data (FSF 2021, FSF 2020) using a US-wide estimate of combined tidal, pluvial, fluvial, and surge risk at different return periods [18]. Studies comparing these two measures have documented social and geographical variation in "risk difference" measures and use NFIP claims to show how NFIP depth estimates underestimate exposure probability [17] and how homeowners underestimate and undervalue long-term flood risk [14].

The challenges with risk estimation and risk perception contribute to problems with adverse selection in property and insurance markets [14,19,20]. Such problems are relevant for this study because, in the US, the flood insurance market is the quasi-public FEMA NFIP and homes with federally backed mortgages within SHFAs are required to carry flood insurance [1]. Despite this mandate, and due to the "risk difference" and measurement challenges, we hypothesize that both areas with a greater number of homes in the SFHA will experience more insurance uptake and exposure and those areas with "risk differences", where SFHA underestimates risk versus alternative measure, will have even greater probabilities of flood exposure.

1.1.2. Social Vulnerability and Disparate Exposure

Social vulnerability within the flood hazard context refers to the degree to which people can be harmed by a flooding event involving demographic and socioeconomic characteristics, such as race and income, that may make certain groups disproportionately likely to be exposed [10,21]. Studies of social vulnerability and disparate exposure are generally conducted at the county or census tract level and have found some evidence that higher populations of lower income, Hispanic, and Black residents are associated with greater probabilities of exposure [3,10–12]. Similar patterns emerge from risk-based studies [22,23], and parcel-level studies of risk also predict higher levels of risk for lower-income suburban black census tracts, especially in the Southeastern US [13,16]. Likewise, both event studies of different models of risk ("risk difference", e.g., SFHA v. FSF Flood Factor) focusing on exposure outside of the SFHA in single events [3] (flooding in Houston, 2017) and studies of estimated risk [24] find patterns of greater exposure for lower-income and minority populations in areas where the SFHA underestimated risk when compared to FSF's increased estimates of long-term risk (FSF Flood Factor).

Given that risk-based analysis related to flooding suggests that flood hazard risk is influenced by demographic vulnerability indicators such as income, race, and insurance coverage, we hypothesize that indicators of social vulnerability will also predict flood exposure. Furthermore, this study used NFIP insurance coverage as a response to test these same hypotheses and to control for propensities in coverage due to its possible endogeneity with NFIP claims as a measure of exposure. We hypothesize that indicators of vulnerability and "risk difference" will be more strongly correlated with exposure, while less socially vulnerable places will have greater levels of NFIP coverage.

1.1.3. Urban Form

Beyond social vulnerability, studies have identified urban form as another driver of flood exposure in the Gulf of Mexico region. Urban form and structure refer to the layout and organization of cities, including housing development and economic activity. High population density and economic activity have a significant influence on the distribution and magnitude of risk [2]. Flood risk is typically associated with elevation and hydrology; only recently has urban form and structure been considered a contributor to flood risk, finding it to be increased in lower-density suburban areas [13]. This could be because, in the U.S. context, zoning and transportation decisions tend to limit the ability to intensify land use intensity, effectively making the supply of housing land less elastic per unit of land. In the Gulf of Mexico region, the supply of low flood-risk land is limited. Because of first-mover advantages [25], we hypothesize that older areas will be less exposed to flooding because, across a limited-density, flood-prone landscape, older development would have occupied the least hazard-exposed areas. Furthermore, the NFIP may have created a moral hazard, leading to increased floodplain development since its creation in the 1960s.

Accordingly, local differences in urban form, such as density and housing age, may be important and correlate with both insurance coverage and exposure [11]. We considered differences in urban form and tested if they have significant explanatory power of the variance in flood exposure in gulf communities. We also ask if risk differentials impact coverage and exposure in census tracts with more suburban densities and newer housing stock. Therefore, we explored the relationship between urban form characteristics, population density, housing stock age, flood zone densities, and significant flood exposure in the Gulf Coast region in the past ten years. Understanding these patterns may contribute to better knowledge of urban planning and contribute to flood risk reduction over the long term. We hypothesize that census tracts with lower densities and newer housing stock will have higher flood exposure propensities.

1.1.4. Scale and Heterogeneity

Longitudinal empirical data across regions can reveal notable patterns otherwise not captured using other methods [8,24], raising the question of whether the most important urban form and social correlates of flooding happen at a regional (e.g., MSA, commuting zone), county, or neighborhood (census tract) level. Empirical data on coverage and exposure at the census tract level can help to assess regional versus local contributions of scale and its relationship to estimates of flood exposure. Investigating the significant geographical scale of exposure can reveal nuances in terms of the drivers and potential policy solutions to promote resilience [21]. Is variation in exposure driven by the scale of entire regions (e.g., a problem for greater Houston and New Orleans), specific counties (e.g., Orleans Parish or Harris County), or neighborhoods?

We hypothesize that because landscapes in the Gulf Coast vary over large geographic scales but are all relatively flat and low elevation, regional and county level variations will be significant drivers of insurance coverage and exposure and that shoreline counties will have greater exposure than inland areas. However, because localized risk conditions and social vulnerability tend to differentiate at the neighborhood level, census tract-level variations in social vulnerability, risk, and “risk difference” will be important secondary contributors to exposure and coverage.

To test these hypotheses, our article proceeds by first describing in Section 2 the materials and methods used, describing the case study area, data assembly, and analysis methods; we then present the results of both insurance coverage and exposure models in Section 3. We discuss those results in terms of our hypothesis and current literature in Section 4 and provide, in Section 5, conclusions, summarized insights, and next steps. Our research contributions include (1) novel approaches to comparatively modeling neighborhood estimates of flood exposure and flood insurance, (2) testing the relationship between indicators of social vulnerability and flood exposure and insurance coverage and providing, (3) a clearer understanding of the importance of local neighborhood risk, urban form, and social vulnerability indicators versus regional patterns of flood exposure and insurance coverage. This provides a clearer picture of the interaction between flood exposure and a major driver of flood vulnerability in the United States, underinsurance.

2. Materials and Methods

To address the questions and hypothesis described above, we use a multilevel modeling approach for census tracts within counties and regions (commuting zones) in the Gulf of Mexico adjacent areas (see Figure 1, Map of Gulf of Mexico Study Area) during two recent time periods (2010–2014, and 2015–2019). A focus on this broader area is merited because the Fourth National Climate Assessment describes the southeastern region as more vulnerable to dangerous changes in climate and a larger area facing disproportionate impacts of climate hazards since the mid-20th century [1]. Many parts of the region face a current insurance crisis and higher flood insurance rates under Risk Rating 2.0. In addition, the Gulf Coast is an area of high socioeconomic disparity.

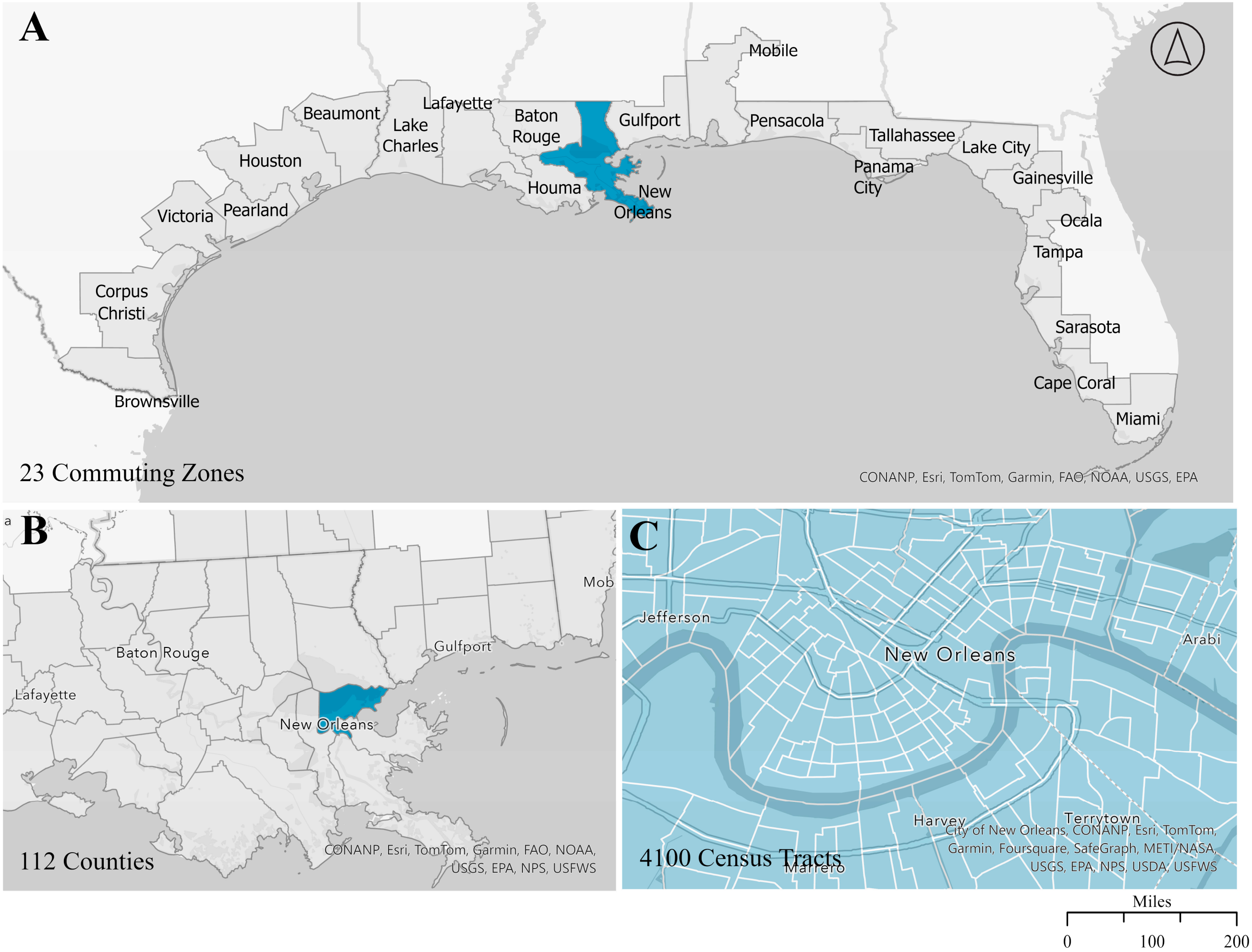

Figure 1. Map of Gulf of Mexico Study Area with (**A**) commuting zones, (**B**) counties, and (**C**) census tracts. The map shows a dynamic view of the scale differences in the study areas, using Orleans Parish as an example.

2.1. Study Area Inclusion Criteria

To address our questions about regional vulnerability, we use the 1990 Commuting Zone delineations provided by the Economic Research Service of the United States Department of Agriculture. Commuting zones (CZs) are helpful geographic units meant to delineate local economies at a larger localized scale that conserves economic characteristics (Tolbert and Sizer, 1996). Our study area includes 23 CZs between Texas, Louisiana, Mississippi, Alabama, and Florida. Coastal Watershed Counties, defined by NOAA's Office of Coastal Management, act as a recognizable framework to describe human dimensions along the coast. For this study, we selected each coastal county within the states of Texas, Louisiana, Mississippi, Alabama, and Florida. In addition, NOAA also delineates whether the coastal counties are adjacent to a distinguishable shoreline or, in our study, the Gulf of Mexico; coastal counties that meet this criterion are labeled as Coastal Shoreline Counties (NOAA). Our study includes 112 unique counties with available data. The minimal spatial unit in this study is at the census tract level. We use the 2010 census tract delineations provided by the Census Bureau. Census tract-level data have the granularity necessary to address our exposure objectives. We were able to find available census data for 4055 tracts. If a census tract had incomplete census data or NFIP data, the tract was excluded from the study. We removed 13% of the tracts from the original boundary.

2.2. Data Sources and Descriptive Statistics

Our data structure is like Noonan et al. (2023), except that it focuses on the Gulf of Mexico, encompasses two periods (2010–2014 and 2015–2019), and uses risk and "risk difference" as explanatory variables in two sets of models, one of insurance coverage, and a second of flood exposure. Here, we present our data sources (Table 1—Variable descriptions and data sources), the process for computing and processing them, and summary statistics for each one. As we describe below, we also examine models of counties we define as "Exposed Counties," region-county combinations with significantly higher claims in the study periods. Descriptive statistics for those models can be found in Appendix A Table A1. We have made the R script of the process "input_build.R" and supporting data files available at the project GitHub repository (https://github.com/LSU-EPG/-Insurance-Coverage-and-Flood-Exposure-in-the-Gulf-of-Mexico (accessed on 19 August 2024)).

Table 1. Variable descriptions and data sources.

Variable Name	Definition	Data Source
Dependent Variables		
NFIP Insurance Claims	The number of insurance claims made in the tract in a time period.	National Flood Insurance Program Redacted Claims.
Social Vulnerability		
NFIP Insurance Coverage Index	Percent of insurance coverage in a tract. Number of active NFIP policies divided by total housing units.	National Flood Insurance Redacted Claims.
Median Income	Tract median household income (thousand dollars).	US Census Bureau; American Community Survey, 2010 American Community Survey 1-Year Estimates.
Black Residents	Percentage of Black residents in a tract.	US Census Bureau; American Community Survey, 2010 American Community Survey 1-Year Estimates.
Hispanic Residents	Percentage of Hispanic residents in a tract.	US Decennial Census of Population and Housing, 2010
Renter Occupied Housing	Percent of tract housing units that are renter-occupied.	US Census Bureau; American Community Survey, 2010 American Community Survey 1-Year Estimates.
Risk		
SFHA	Percentage of structures that fall within a Special Flood Hazard Area (SFHA) is a region designated by FEMA as an area with a 1% annual chance of flooding (also known as the 100-year flood zone).	FEMA (DFIRMs downloaded June 2022).
Risk Difference	Pct. Structures SFHA—Pct. Structures >= F.F. 3.	
Urban Form		
Shoreline County	A discrete indicator of a coastal county that is adjacent to the shoreline of an ocean, estuary, river, etc.	National Oceanic Atmospheric Administration, Office of Coastal Management.
Age of Housing Stock	Median Year houses in the tract were built.	US Census Bureau; American Community Survey, 2010 American Community Survey 1-Year Estimates.
Population Density	Persons per square mile in the tract, calculated by dividing the total population by land area,3 Levels: Low Density(Suburban), Moderate and High Density(Suburban and Urban), Very Low Density(Rural).	US Census Bureau; American Community Survey, 2010 American Community Survey 1-Year Estimates.
Scale		
Commuting Zone	Labor market unit meant to geographically characterize the local labor market.	United States Department of Agriculture: Economic Research Service.
Counties	A political and administrative division of a state that provides certain local governmental services.	
Census Tracts	A small geographic area within a county or similar entity that is used to collect census data and approximate the scale of a neighborhood.	

2.2.1. Response Variables

Insurance Index—NFIP Policies

We designed an insurance coverage variable to use as a dependent variable in our coverage models. To calculate insurance coverage for each census tract, we use NFIP Redacted Insurance Policies and ACS Total Housing Unit from the Census Bureau. We first summarize the number of active NFIP policies per year in each census tract between 2010 and 2019. We then retrieved the total number of housing units at the end of 2014 and 2019. We divided the yearly average of active policies by the total number of housing units at the end of each of our time periods. For interpretability and modeling reasons, we scaled this variable using the scale() Function in R. For robustness, we calculated a second set of models for counties where we identified potential data quality issues, but these were not significantly different. For a detailed explanation, see the R script of the process "input_build.R" and at the project GitHub repository (https://github.com/LSU-EPG/-Insurance-Coverage-and-Flood-Exposure-in-the-Gulf-of-Mexico (accessed on 19 August 2024)). This dataset has some degree of additional random error introduced by FEMA for privacy reasons, but the policies are reported at a Census tract level, and we do not think the process of reassignment of some policies to different census tracts biases our models because it was performed randomly, but it may reduce the accuracy of estimates.

As can be observed in Table 2—Descriptive statistics, our Gulf-wide Summary statistics for Gulf-wide models data show a yearly average of 47% flood insurance coverage in our study area between the years 2010 and 2019. A map of estimated coverage intensity is presented in Figure 2.

Table 2. Summary statistics for Gulf-wide models.

Characteristic	N	Mean (SD)	Median (IQR)
Insurance Claims	8110	33 (110)	4 (18)
Insurance Coverage	8110	7 (10)	3 (8)
Vulnerability: Median Household Income	8110	54,362 (25,380)	49,037 (26,922)
Vulnerability: % Black Population	8110	18 (24)	8 (22)
Vulnerability: % Hispanic Population	8110	22 (25)	12 (25)
Vulnerability: % Renter Occupied	8110	34 (20)	30 (27)
Risk: SFHA	8110	23 (29)	10 (31)
Risk: Risk Difference	8110	−16 (31)	−7 (21)
Urban Form: Median House Age			
Before 1950	247 (3.0%)	247 (3.0%)	247 (3.0%)
1950–1969	1484 (18%)	1484 (18%)	1484 (18%)
1970–1989	4162 (51%)	4162 (51%)	4162 (51%)
After 89	2217 (27%)	2217 (27%)	2217 (27%)
Urban Form: Density Category			
Low Density (Suburban)	2249 (28%)	2249 (28%)	2249 (28%)
Moderate and High Density (Suburban and Urban)	3665 (45%)	3665 (45%)	3665 (45%)
Very Low Density (Rural)	2196 (27%)	2196 (27%)	2196 (27%)
Urban Form: Shoreline County			
0	1150 (14%)	1150 (14%)	1150 (14%)
1	6960 (86%)	6960 (86%)	6960 (86%)

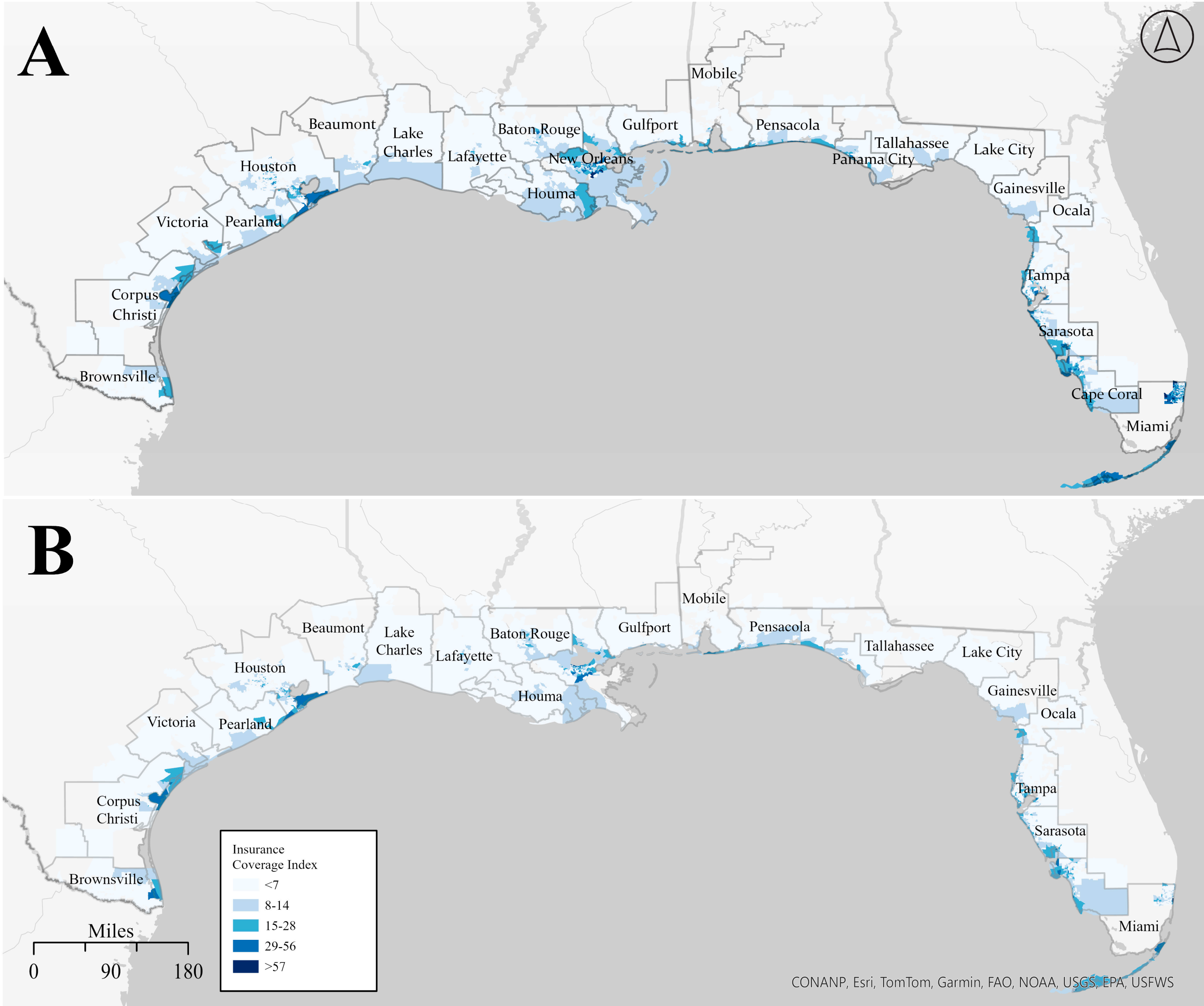

Figure 2. Gulf of Mexico Study Area estimated NFIP Insurance Coverage Index. (**A**) Estimated active NFIP policies divided by total housing units between 2010 and 2014 per census tract and (**B**) Estimated active NFIP policies divided by total housing units per census tract between 2015 and 2019.

Insurance Claims—NFIP Claims

We use total claims as a response against our fixed predictors. We use National Flood Insurance Redacted Claims to summarize the total number of insurance claims made in a census tract between the years 2010 to 2014 and again for 2015–2019. These data are increasingly used to model flood exposure [7]. They are reported with exact filing dates so that they could be summarized at different temporal scales, but we chose 5-year periods to better estimate cumulative exposure risk and reduce the amount of randomness that would be present if claims were modeled monthly, given the zero inflation of the dataset. There is precedent for this approach in models of flood exposure based on changes in wetland land cover [8].

NFIP Redacted Claims data can be downloaded from FEMA's open-access website. This census tract-level dataset includes the number of flood insurance claims made in every tract in the country since 1950. Flood insurance claims made between 1 January 2010 and 31 December 2019 were extracted and filtered for each of the states in the study area: Texas, Louisiana, Mississippi, Florida, and Alabama. A map of claims per census tract for each time period is presented in Figure 3.

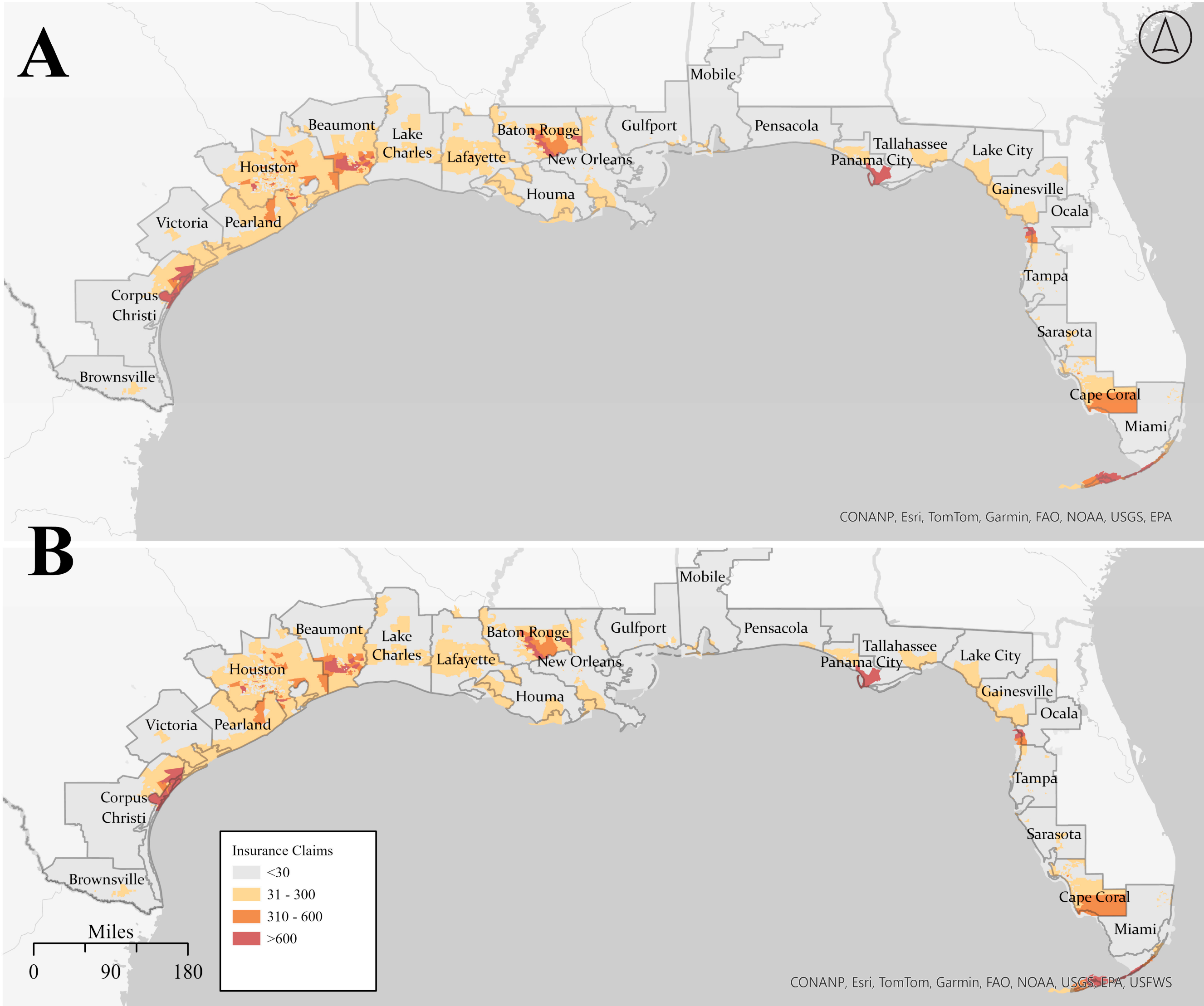

Figure 3. Gulf of Mexico Study Area NFIP insurance claims. (**A**) Total count per census tract between 2010 and 2014 and (**B**) total count per census tract between 2015 and 2019.

2.2.2. Independent Variables

The independent variables used in this analysis draw on Noonan et al. (2022) and leverage Census ACS data (2010–2014, 2015–2019) data from the National Risk Index that summarizes the percentages of structures per tract intersecting with the National Flood Hazard Layer dataset, and First Street Foundation (FSF) Flood Factor Estimates. We combine these and other sources to compute a set of Social Vulnerability Variables, Risk Variables, and Urban Form Variables, as described in Table 2. As with the response variable, we present our code for assembling these variables in our project GitHub repository (see https://github.com/LSU-EPG/-Insurance-Coverage-and-Flood-Exposure-in-the-Gulf-of-Mexico/tree/main (accessed on 19 August 2024)).

Median household income acts as a social vulnerability predictor in each model. We retrieve the median household income for each census tract from the ACS 2010 census. We summarize the average median household income for each of the census tracts in each of our time periods. The mean household income calculated gulf-wide in this study is $54,362 per year with a standard deviation of $25,380 per year.

Race

Racial composition is used as a fixed social vulnerability predictor for each model. We retrieve the number of Black and Hispanic residents in a census tract in each of our ACS years. We then divide the number of either Black or Hispanic residents by the total number of residents in the entire census tract for that year and multiply that number by 100 to get a percentage. We then obtain the percentage of residents in each census tract that identify as Black or Hispanic for two racial composition predictors. For this study, we exclude the percentage of white residents in the tracts as a reference category, as well as other reported groups, due to low representation rates in many of the regions in our study area. We calculate the mean percent of black residents in a census tract to be 18% with a standard deviation of 24%. We calculate that Hispanic residents make up 22% of the census tract population on average, with a standard deviation of 25%.

We used the percentage of renter-occupied housing units as a fixed social vulnerability predictor in each model. To calculate this, we divided the number of renter-occupied housing units by the total housing units in a census tract.

Risk

Floods are affected by the environment, and the broader context of this study includes relatively similar low-lying areas in the Gulf of Mexico region. To control for environmental propensity for flooding, we used a tract level variable from the National Risk Index representing the proportion of structures within a Special Flood Hazard Area (SFHA), which provides a fixed flood risk predictor in each of our models. The SFHA is where the National Flood Insurance Program (NFIP) enforces the mandatory purchase of flood insurance because these areas are within floodplains susceptible to inland flooding. We added the percentage of each tract that is in either A or V zones. This gives us a measure of the localized flood risk; 23% of our average census tract falls within an SFHA with a standard deviation of 29%.

Other environmental predictors of flood risk produce different estimates, potentially more accurate and including long-term risk from climate change. Following Noonan et al. (2022), we test how the difference between SFHA delineations and Flood Factor Scores by computing a percentage of structures with flood factor scores (Moderate and above) roughly analogous to the return periods used for the SFHA. We do this to examine whether there are significant correlations between estimated coverage, a potential indicator of adverse selection in insurance markets (Wagner, 2022), and exposure, a potential indicator of information deficits for different groups in terms of exposure risks. We measure an average risk difference of −16% and a standard deviation estimated to be 30%.

To describe the population density, we created three categorical fixed predictors in each model. We retrieved the total population of each tract and divided it by the land area to get persons per square mile. Census tracts with less than 1000 people per square mile represent our low-density rural areas, while census tracts with more than 3000 people per square mile represent our moderate to high-density suburban to urban areas. Census tracts that fall between this range represent our low-density suburbs. Moderate to high-density suburban and urban areas act as a reference category for modeling. We computed this variable due to the observation that lower-density suburban areas faced greater risk (Tate 2021). Our sample has 45% of tracts falling into moderate to high densities, 27% belonging to the low-density suburban areas, and 28% of the tracts seeing a lower rural density; see Table 2 for standard deviations and median densities of each group.

We retrieved the median house age of each census tract and created a factorized fixed predictor for the models. We wanted to capture different eras of the housing market development and how they might correlate with coverage and exposure due to our hypothesis about older areas occupying areas of lower risk. The categories were designed as follows:

Homes built before 1950, Homes built between 1950 and 1969, Homes built between 1970 and 1989, Homes built after 1989.

The Gulf of Mexico has a flat geography with combined pluvial, fluvial, and coastal flood risks. Due to this, as well as previous research on NFIP, we hypothesized that coastal counties would have categorically greater exposure probabilities. Our models include an indicator variable for census tracts in counties identified as "Coastal Shoreline County." As shown in Table 2, 86% of the census tracts in our study sample are within a "Coastal Shoreline County" based on NOAA's Office of Coastal Management.

2.3. Modeling Technique

We designed two multilevel generalized linear models to test our hypotheses following the linear modeling workflow presented by [26]. The workflow provides replicable and adaptable scripts that can produce appropriate graphical outputs to guide the user along model refinement. Our models combine fixed effect predictor variables, random predictor variables, and temporal data structure to meet our objectives. We use a nested cross-random effects approach to control for Commuting Zone and county effects and test how tract-level covariates correlate with insurance coverage and NFIP claims as a measure of exposure. Our model of "Exposed Counties" selects counties with significantly positive effects on exposure and replicates the model technique on the subset to examine if fixed predictors vary. We explore the distribution of all our variables to check for outliers. The features of our response variables provide insight into the recommended families and link functions for our model formulation. To test for the independence of our two models, we tested that exposure and insurance coverage were sufficiently independent, see Appendix A, Figure A1: Correlation Matrix between NFIP Claims, estimated NFIP Policy Count, and estimated NFIP Insurance Coverage.

2.3.1. Gulf-Wide NFIP Insurance Coverage Model

The Gulf-wide coverage model uses the insurance coverage index as a single continuous response variable. Raw data revealed a significant right-skewed distribution and extreme values. This model specifies a Gamma response with a log link scale. We use social vulnerability, risk, time, and urban form variables as fixed predictors. We include a nested random intercept in our model to estimate the differences between Gulf-wide insurance coverage and regional insurance coverage [26]. A zero-inflation argument is added to this model to consider the excess of zeros across the fixed predictor value (Equation (1)).

$$IC_{ij} \sim \begin{cases} 0 \ \ with\ probability\ \pi_{ij} \\ IC^{*}_{ij}\ with\ probability\ 1-\pi_{ij} \end{cases} \quad (1)$$

$$*IC_{ij} \ \sim \ Gamma(\alpha_{ij},\ \beta_{ij})$$

$$log(\alpha_{ij}) = X^{T}_{ij}\beta_1 + u_{1j}$$

$$log(\beta_{ij}) = X^{T}_{ij}\beta_2 + u_{2j}$$

where IC_{ij} denotes the Insurance Coverage index that corresponds to our response variable for the i census tract in the j group. α_{ij} and β_{ij} are Gamma distribution parameters for the i census tract in the j group and π_{ij} represents the zero-inflation probability for the i census tract in the j group. The random effects u_j capture the group-level variability that influences the parameters α_{ij}, β_{ij}, and π_{ij}. $X\_ij^\prime$ are the corresponding fixed effect variables for the i individual in the j group. β_1 and β_2 are the vectors of the fixed-effect coefficients, and u_{1j} and u_{2j} are the random effects associated with the j group. For the gulf-wide insurance coverage index model, the random effects are accounted for by the CZ and county, which represents the nested random effect. On the other hand, for our exposed counties models, the random effects are accounted for by the counties. All analyses were performed using R Statistical Software (R version 4.3.1; R Core Team 2021)

2.3.2. Gulf-Wide Exposure Model

The Gulf-wide exposure (NFIP claims) model uses total claims as a single response count variable (Equation (2)). Gulf-wide claims follow a negative binomial response distribution with a log link scale. The insurance coverage index for each tract-time period combination is added to the insurance claim model as a fixed social vulnerability predictor. The model is otherwise similar to the Gulf-wide insurance coverage index model.

$$E_{ij} \sim NegBin(\mu_{ij}, \varnothing) \tag{2}$$

$$log(\mu_{ij}) = X_{ij}^{T}\beta_1 + u_{ij}$$

where E_{ij} denotes the exposure represented by the total count of claims each time as a response variable for the i census tract in the j group. μ_{ij} denotes the mean of the negative binomial distribution and $\varnothing$ represents the dispersion parameter, which controls the variance of the distribution. $X\_ij\hat{}$ are the corresponding fixed-effect variables for the i census tracts in the j group and β_1 is the vector of the fixed-effect coefficients, and u_{ij} is the random effect associated i census tract in the j group. The random effects in this model follow a similar grouping to those described in the description of Equation (1).

2.3.3. Exposed Counties NFIP Coverage Model

The Exposed Counties coverage model is designed to address our hypothesis on the relationship between geographic scale and flood exposure in the southeast region. The Gulf-wide coverage sample is reduced to include the counties that fall into the third quartile of random intercept estimates, 0.67 and above, from the Gulf-wide exposure (NFIP claims) model. The random intercept is unnested, using the county as the sole level. Exposed Counties insurance follows a similar trend as the Gulf-wide model, allowing us to conserve the model design.

2.3.4. Exposed Counties NFIP Claim Model

The Exposed Counties claim model is the final model, and arguably the most interesting, model of this study. Using the same counties extracted from the Gulf-wide test of this, this model also adapts an unnested county random effect. The fixed social vulnerability, risk, urban form, and time variables are added to this model.

3. Results

3.1. Random Effects and Model Fit for All Models

Here, we report random effects and overall model fit statistics for our four models. We use the marginal and conditional R squared to assess how much variance in the corresponding response variables was being accounted for by fixed effects (marginal) and fixed effects plus random effects (conditional).

For the insurance coverage index models, we found a marginal R of 0.499 for the Gulf-wide model and 0.534 for the Exposed Counties model. This suggests that without the random effects, our fixed predictors explain 50% and 53% of the variance in the total number of insurance claims made in a census tract. When we consider the spatial random effects with the fixed effects, we find that the explanatory power of both models increases. The Gulf-wide model explains 75% of the variance in the response and 68% of the variance in the most exposed counties (see Table 3—Insurance coverage index regression results).

For the exposure (NFIP claims) model, we found a marginal R of 0.37 for the Gulf-wide model and 0.648 for the Exposed Counties model. This suggests that without the spatial random effects, our fixed predictors explain 37% and 65% of the variance in our insurance coverage index. When we consider the spatial random effects with the fixed, we see the explanatory power of both models increase to about 70% (see Table 4—Insurance claims exposure regression results).

Table 3. NFIP coverage regression results.

	Gulf-Wide Coverage			Exposed Counties Coverage		
Predictors	Estimates	Std. Error	CI	Estimates	Std. Error	CI
Vulnerability: Median Household Income	1.41 ***	0.02	1.37–1.46	1.63 ***	0.06	1.51–1.76
Vulnerability: % Black Population	0.88 ***	0.01	0.86–0.90	0.80 ***	0.02	0.76–0.84
Vulnerability: % Hispanic Population	0.80 ***	0.01	0.78–0.83	0.97	0.03	0.91–1.02
Vulnerability: % Renter Occupied	0.89 ***	0.01	0.87–0.91	1.12 ***	0.03	1.06–1.18
Shoreline County	3.31 ***	0.47	2.51–4.37	2.49 ***	0.45	1.75–3.55
Risk: SFHA	1.83 ***	0.02	1.79–1.87	1.79 ***	0.04	1.71–1.88
Risk: Risk Difference	0.77 ***	0.01	0.75–0.79	0.84 ***	0.02	0.80–0.88
Urban Form: Low Density (Suburban)	0.94 **	0.02	0.90–0.98	1.04	0.06	0.93–1.16
Urban Form: Very Low Density (Rural)	0.81 ***	0.02	0.77–0.86	1.03	0.07	0.91–1.17
Urban Form: Homes Built Between 1950 and 1969	1.15 *	0.07	1.03–1.30	1.53	0.34	0.99–2.37
Urban Form: Homes Built Between 1970 and 1989	1.28 ***	0.08	1.14–1.44	1.57 *	0.35	1.02–2.41
Urban Form: Homes Built After 1989	1.28 ***	0.08	1.13–1.44	1.45	0.33	0.94–2.25
Time Period: 2015–2019	0.67 ***	0.01	0.64–0.69	0.76 ***	0.03	0.70–0.81
Random Effects						
σ^2		0.52			0.41	
τ_{00}		0.47 $_{\text{Commuting·Zone:County}}$			0.20 $_{\text{County}}$	
ICC		0.47			0.32	
N		23 $_{\text{Commuting·Zone}}$ 112 $_{\text{County}}$			29 $_{\text{County}}$	
Observations		8110			1325	
Marginal R^2/Conditional R^2		0.513/0.743			0.584/0.718	
AIC		37,991.809			5635.723	

Note(s): * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. NFIP Claims (flood exposure) regression results.

	Gulf-Wide Claims			Exposed County Claims		
Predictors	***Incidence Rate Ratios***	***Std. Error***	***CI***	***Incidence Rate Ratios***	***Std. Error***	***CI***
Coverage	1.04 ***	0.00	1.03–1.04	1.12 ***	0.02	1.09–1.15
Vulnerability: Median Household Income	1.07 *	0.03	1.01–1.13	1.00	0.08	0.85–1.17
Vulnerability: % Black Population	1.03	0.02	0.99–1.08	1.29 ***	0.07	1.15–1.44
Vulnerability: % Hispanic Population	0.97	0.03	0.92–1.03	1.12 *	0.06	1.00–1.25
Vulnerability: % Renter Occupied	0.91 ***	0.02	0.87–0.96	0.79 ***	0.05	0.70–0.90
Shoreline [1]	1.90 **	0.44	1.20–3.01	1.80 ***	0.28	1.33–2.43
Risk: SFHA	1.64 ***	0.04	1.57–1.72	1.39 ***	0.09	1.22–1.58
Risk: Risk Difference	0.91 ***	0.02	0.87–0.96	0.89 *	0.05	0.80–1.00
Urban Form: Low Density (Suburban)	1.08	0.05	0.99–1.18	1.09	0.14	0.85–1.39
Urban Form: Very Low Density (Rural)	1.22 ***	0.07	1.09–1.37	1.50 **	0.22	1.12–2.00
Urban Form: Homes Built Between 1950 and 1969	1.55 ***	0.18	1.23–1.96	1.11	0.56	0.41–3.00
Urban Form: Homes Built Between 1970 and 1989	1.73 ***	0.20	1.38–2.17	1.52	0.76	0.57–4.06
Urban Form: Homes Built After 1989	1.77 ***	0.21	1.39–2.24	1.64	0.83	0.61–4.45
Time Period: 2015–2019	5.51 ***	0.22	5.09–5.96	4.52 ***	0.47	3.69–5.54
Random Effects						
σ^2		1.04			1.11	
τ_{00}		1.20 $_{\text{Commuting.Zone:County}}$			0.06 $_{\text{County}}$	
ICC		0.53			0.05	
N		23 $_{\text{Commuting.Zone}}$ 112 $_{\text{County}}$			29 $_{\text{County}}$	
Observations		8110			1325	
Marginal R^2/Conditional R^2		0.374/0.708			0.557/0.579	
AIC		56971.398			12051.780	

Note(s): * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 4 depicts a bivariate map comparing these results for our Gulf-wide models. Significant positive CZ-county level effects for the insurance coverage index model suggest areas of relatively high insurance coverage, and areas positive CZ-county level effects in the exposure (NFIP claims) model suggest areas with significant flood exposure. High-low counties on the map may have relatively less insurance coverage based on their exposure patterns in our study period.

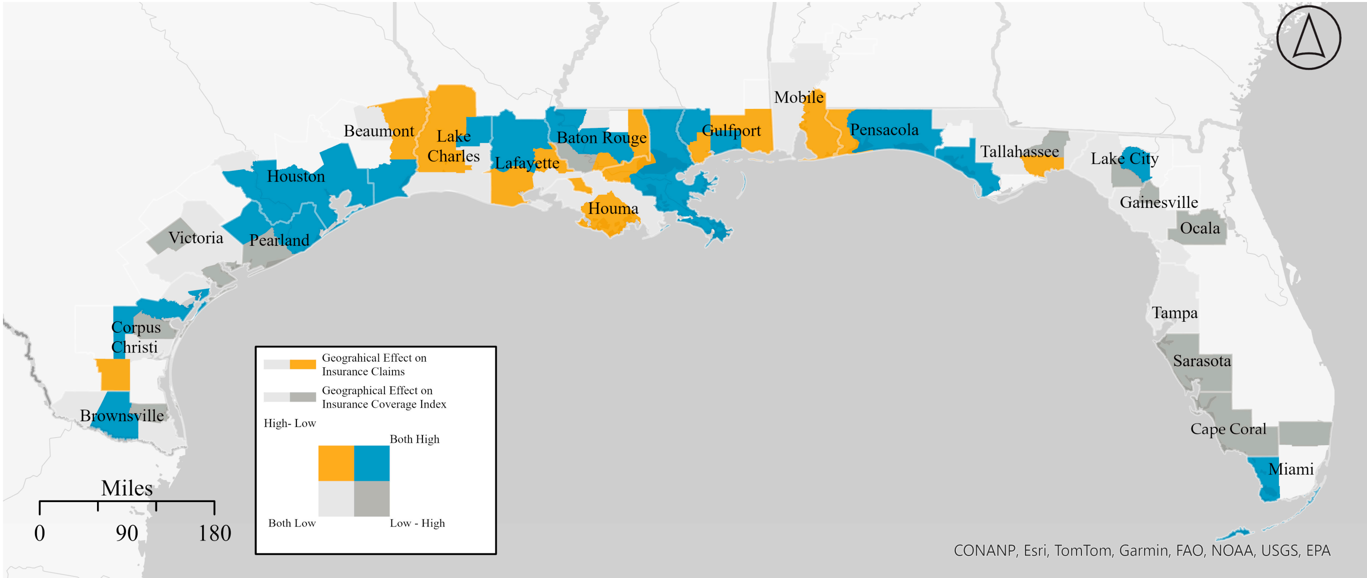

Figure 4. This map depicts a bivariate comparison of the effect size of random effect predictors, represented by counties, between the insurance coverage index model and the exposure model.

3.2. NFIP Insurance Coverage Models

In our NFIP insurance coverage index models, we report the exponentiated beta coefficients and confidence interval for our fixed and random effects and how, with all other variables held constant, the estimate shows how much the predictor is estimated to change the response or insurance coverage index (see Table 3—Insurance coverage index regression results).

3.2.1. Social Vulnerability—Insurance Coverage Index Models

Income—Insurance Coverage Index Models

Median household income shows a positive association with the insurance coverage index for both the Gulf-wide coverage model (odds ratio: 1.41 CI [1.37–1.46]) and the exposed counties model (1.39 CI [1.32–1.47]). This suggests that tracts within a shoreline county with a median household income of $28,000 a year are predicted to have an insurance coverage index of 2.19%; this is lower than the predicted insurance coverage index of 3.06% of the mean median household income, $54,362 a year.

Black Residents—Insurance Coverage Index Models

The percentage of black residents in a tract is negatively associated with our insurance coverage index Gulf-wide (0.88 CI [0.86–0.90]) and within exposed counties (0.80 CI [0.76–0.84]). This suggests that a tract inside of a shoreline county with 45% Black residents is predicted to have an insurance coverage index of 2.65%, 0.38% less than a tract in a shoreline county where 20% of its residents are Black.

Hispanic Residents—Insurance Coverage Index Models

The percentage of Hispanic residents in a tract is also negatively associated with our insurance coverage index Gulf-wide (0.80 CI [0.78–0.83]) but non-significant within exposed counties. The Gulf-wide model suggests that tracts within a shoreline county with the estimated mean percent of Hispanic residents (22%) are predicted to have an insurance coverage index of 3.06%, this is 0.64% lower than tracts in similar areas but where 1% of its residents are of Hispanic descent.

Renter-Occupied Housing Units—Insurance Coverage Index Models

Renter-occupied housing units show a negative effect on the insurance coverage index Gulf-wide (0.89 CI [0.87–0.91]). Gulf-wide, the model predicts that a tract in a shoreline county with 15% renter-occupied housing units has an insurance coverage index of 3.42%, while a tract with 55% renter-occupied housing units is predicted to have an insurance coverage index of 2.71%. The exposed counties model shows a positive influence on our insurance coverage index (1.12 CI [1.06–1.18]), suggesting a tract in a shoreline county with 55% renter-occupied housing units is predicted to have an insurance coverage index of 3.16%; this is 0.72% higher than a tract with 15% renter-occupied housing units.

3.2.2. Risk—Insurance Coverage Index Models

The percentage of structures in a flood hazard area in a tract shows a positive relationship to estimated insurance coverage index the coverage for both models, Gulf-wide (1.83 CI [1.79–1.87]) and exposed (1.79 CI [1.71–1.88]). For both models, this suggests that tracts in a shoreline county where 23% of the structures lay in a flood zone are predicted to have an insurance coverage index of 2.90%; this is estimated to be 2.86% lower than tracts with 50% of the structures in an SFHA.

The difference between risk measures SFHA and Flood factor shows a negative relationship to the insurance coverage across the coverage models where Gulf-wide we see a beta estimate of 0.77 CI [0.75–0.790] and exposed counties producing a beta estimate of 0.89 CI [0.86–0.92]. When flood factors measure more properties at risk than SFHA, we can expect insurance to decrease by 0.55% Gulf-wide and 0.19% within exposed counties.

3.2.3. Urban Form—Insurance Coverage Index Models

The age of the housing stock in a census tract shows a positive relationship to the insurance coverage index. Homes built after 1989 produce an estimate of 1.28 CI [1.14–1.44]; this is the most significant category for the Gulf-wide model. This estimate suggests that a tract in a shoreline county where the majority of the homes are built after 1989 is predicted to have an insurance coverage index of 3.91%, which is 0.85% higher than a census tract where the homes were built before 1950. The exposed counties coverage models did not produce significant estimates for any of the other housing stock categories.

The number of people per square mile shows a negative relationship to our insurance coverage index. When compared to moderate-density suburban–urban tracts inside of a shoreline county, very low-density rural tracts also in a shoreline county produce a beta estimate of 0.81 CI [0.77–0.86], suggesting that the predicted insurance coverage index is 2.48%. The predicted insurance coverage index for tracts with fewer than 1000 persons per square mile is 0.58% lower than tracts with more than 5000 people per square mile at 3.06%. Our exposed counties models failed to produce a significant estimate for the population density categories.

Census tracts within a shoreline county have a high positive association with estimated insurance coverage Gulf-wide (3.31 CI [2.51–4.37]) and throughout the exposed counties (2.49 CI [1.75–3.55]). Our Gulf-wide models suggest that with all else health constant, a census tract inside of a shoreline county is predicted to have an insurance coverage index of 3.06%; this is 2.14% higher than a census tract outside of a shoreline county. The exposed counties model suggests that a tract inside of a shoreline county is predicted to have an insurance coverage index of 2.71%, while tracts outside of a shoreline county are predicted to have an insurance coverage index of 1.09%. We note the large confidence intervals for this fixed predictor.

3.3. Exposure (NFIP Claims) Models

As with the insurance coverage index models, here we report the exponentiated beta coefficients (IRR) and confidence interval for our fixed and random effects and how, with all other variables held constant, the predictor influences the behavior in our Gulf-wide and Exposed Counties models of flood exposure (see Table 4—Insurance claims exposure regression results). The Incidence Rate Ratio describes the magnitude and direction of the influence of the predictor on the response variable.

3.3.1. Social Vulnerability—Exposure (NFIP Claims) Models

The proportion of active insurance policies to total housing units in a census tract has a positive influence on the total number of NFIP claims made in that tract in a five-year period. Our Gulf-wide exposure model produces an IRR of 1.04 CI [1.03–1.04], suggesting a census tract inside of a shoreline county with an estimated 0% insurance coverage index is predicted to see 7 NFIP claims made in a 5-year period. If all else is held constant and a tract instead has an estimated 10% insurance coverage index, our model predicts that the total number of NFIP claims made in five years will increase to 10. The exposed counties model produces an IRR of 1.12 CI [1.09–1.15] that suggests that a tract inside of a shoreline county with an estimated 0% insurance coverage is predicted to have 35 fewer NFIP claims made in five years than a similar tract with an estimated 10% insurance coverage index.

Our models suggest that median household income has a positive influence on the total number of NFIP claims made in five years. The Gulf-wide exposure model produces a positive IRR of 1.07 CI [1.01–1.13]. This suggests that a census tract inside of a shoreline county where the median household income is $30,000 a year is predicted to accumulate eight NFIP claims in five years. If the median household income of a similar tract were double, the total claims are expected to be closer to nine. The exposed county exposure model did not produce a significant IRR.

We have evidence that suggests that there is a positive relationship between the percentage of Black residents in a tract and the total number of NFIP claims made in five years. Our exposed counties exposure model produced an IRR of 1.29 CI [1.09–1.15]; this estimate suggests that a census tract inside of a shoreline county where 10% of the residents are Black is predicted to have 25 NFIP claims made in five years, this is five claims less than a tract with 30% Black residents and 12 less than a tract where 50% of the residents are Black. Our Gulf-wide exposure model did not provide significant IRR.

The percentage of Hispanic residents in a tract has a positive relationship to the total count of NFIP claims made in five years. The Gulf-wide exposure model did not produce a significant IRR, but our exposed counties model produced a significant IRR of 1.12 CI [1.00–1.25]. The exposed counties model suggests that a tract inside a shoreline county where 10% of the residents are Hispanic is predicted to see 29 NFIP claims in five years; this is five claims less than a tract where 20% of the residents are Hispanic, and all else is held constant, or 39 NFIP claims.

The percentage of renter-occupied housing units negatively influences the total number of NFIP claims made in a five-year period. The Gulf-wide exposure model produces an IRR of 0.91 CI [0.70–0.90], suggesting a tract in a shoreline county where 10% of the housing units are renter occupied is predicted to have a total count of 10 NFIP claims in five years; this count is predicted to decrease to 8 when 50% of the housing units are renter occupied. The exposed counties exposure model produces an IRR of 0.79 CI [0.70–0.90]; this suggests that a census tract inside a shoreline county where 10% of the housing units are renter-occupied is predicted to see 39 NFIP claims in five years, this count is predicted to decrease to 22 claims when 50% of the housing units are renter occupied.

3.3.2. Risk-Exposure (NFIP Claims) Models

The percentage of structures inside of a special flood hazard area shows a positive influence on the number of NFIP claims made in a census tract in five years. Our Gulf-wide exposure model produces an IRR of 1.64 CI [1.57–1.72], suggesting that a tract where 25% of the structures are in an SFHA is predicted to see nine total NFIP claims in the time period; this is five claims lower than a tract inside a shoreline county where 50% of the structures are in an SFHA, or 14 claims in five years.

The difference between structures in an SFHA and properties with moderate to severe flood risk shows a negative influence on the total count of NFIP claims made in a tract in a five-year period. The Gulf-wide exposure model produces an IRR of 0.91 CI [0.87–0.96], which suggests that in a tract where the SFHA and Flood Factor flood risk are equal, the risk difference is 0, the predicted count of NFIP claims is nine in five years. The model predicts that a risk difference of −20%, meaning that there is more property level FF risk than the SFHA captures, is predicted to see an increase in one claim in five years. The exposed counties exposure model suggests a similar influence (IRR: 0.89 CI [0.80–1.0]), suggesting a −20% risk difference in a tract in a shoreline county is predicted to accumulate three fewer NFIP claims than a tract with a 0 risk difference.

3.3.3. Urban Form—Exposure (NFIP Claims) Models

The proportion of people per square mile shows a positive influence on the total number of NFIP claims made in a five-year window. Our Gulf-wide exposure model produces an IRR of 1.22 CI [1.09–1.37], suggesting that rural low-density tracts inside a shoreline county are predicted to have 9 NFIP claims made by the end of a five-year period, this is 2 NFIP claims less than a high-density suburban–urban tract inside a shoreline county. Our exposed counties model produced an IRR of 1.42 CI [1.17–1.72]. This suggests that a tract with less than 1000 people per square mile (rural low-density) inside a shoreline county is predicted to accumulate 14 more NFIP claims than high-density suburban–urban tracts.

The age of a census tract's housing stock has a positive influence on the total number of NFIP claims made in a five-year period. Homes built after 1989 in our Gulf-wide exposure model produce an IRR of 1.77 CI [1.39–2.24], suggesting that when most homes in a census tract were built after 1989 and are inside of a shoreline county, the predicted count of claims in five years is 16, this predicted to be seven more than tracts inside a shoreline county where the housing stock was built before 1950. Our exposed counties exposure model failed to produce a significant IRR for any of the housing age categories.

Census tracts within shoreline counties have a positive influence on the total NFIP claims made in 5 years. Our Gulf-wide exposure model produces an IRR of 1.90 CI [1.30–2.99]; this estimate suggests a tract inside a shoreline county is predicted to see 9 NFIP claims made in a five-year period. The Gulf-wide exposure model estimate also suggests that tract outside of a shoreline county is predicted to see five claims in five years, four less than those inside. The exposed counties exposure model produces an IRR of 1.80 CI [1.33–2.43], suggesting that a tract inside a shoreline county is predicted to accumulate 13 more NFIP claims in five years than a tract outside of a shoreline county.

4. Discussion

Our models suggest that county and regional (CZ) components of both insurance uptake and exposure are correlated, as seen with the random effects estimates. This is a well-studied trend [6,27,28] related to the spatial correlation of risk. This pattern reflects the fundamental challenge of disaster insurance [29] and contributes to current problems with the NFIP in particular [30], impacting housing markets in the Gulf of Mexico [31]. We note that by modeling two 5-year periods, there is potential randomness in our exposure patterns, as demonstrated by the differences in each period depicted in Figure 3—Gulf of Mexico Study Area NFIP estimated claims per census tract 2010–2014 and 2015–2019.

We observe specific effects in more "shoreline" counties of the region, but not exclusively. When controlling for our insurance coverage index, we observe that places with more coverage have more exposure, even when controlling for risk and other social factors (see Figure 4—Predicted exposure (NFIP claims) versus insurance coverage index), which we think gives credence to [14] Wagner's (2022) reporting significant undervaluation of risk by property owners, and the potential problem of adverse selection. This pattern holds even when controlling for observable risk estimates and potentially increased policies in higher-risk areas (Peralta 2024). Our estimates of the effect of housing stock suggest that census tracts with a median age of homes built after the NFIP program began were more exposed than those with older housing stock.

For urban form, we find that older areas had fewer claims and less coverage. As we control for the insurance coverage index, we do think that there is evidence for older areas facing less exposure and having grown into risk during the process of mass suburbanization after WWII. The role of the NFIP is one question to explore in future research here, but we note that homes built after the advent of NFIP have greater claims relative to the reference category both before and after the NFIP program initiated in the 1960s. However, in our analysis of variation in exposure in exposed counties (NFIP claims), the significance of exposure only begins after 1970, corresponding with the NFIP. Overall, we have evidence that supports the idea that newer homes are at higher risk due to risk areas being occupied as development continues.

For risk, we find that tracts with more structures within the SFHA tend to have higher rates of estimated coverage based on our insurance coverage index and more insurance claims. We expect this pattern as federally-backed mortgages within these two flood zones require participation in the NFIP Program. We see that risk difference follows a different pattern; see Figure 5. Some researchers have criticized the binary nature of the SFHA [17], stating that it underestimates risk. Calculating the importance of the effect of the risk difference variable and comparing its effect on both the NFIP coverage index and observed NFIP claims as a measure of exposure may shed light on the problem of adverse selection in NFIP programs [14]. We also find preliminary evidence that places with greater risk beyond the SFHA have increased participation in NFIP. Likewise, the spatial correlation of coverage and exposure is another problem related to insurance coverage [32], and here again, we observe overlap in the locations of exposure and coverage. We observe that private knowledge about risk is frequently not priced into NFIP premiums is well known, but nonetheless, we think this study can help buttress and clarify those observations in areas near the Gulf of Mexico.

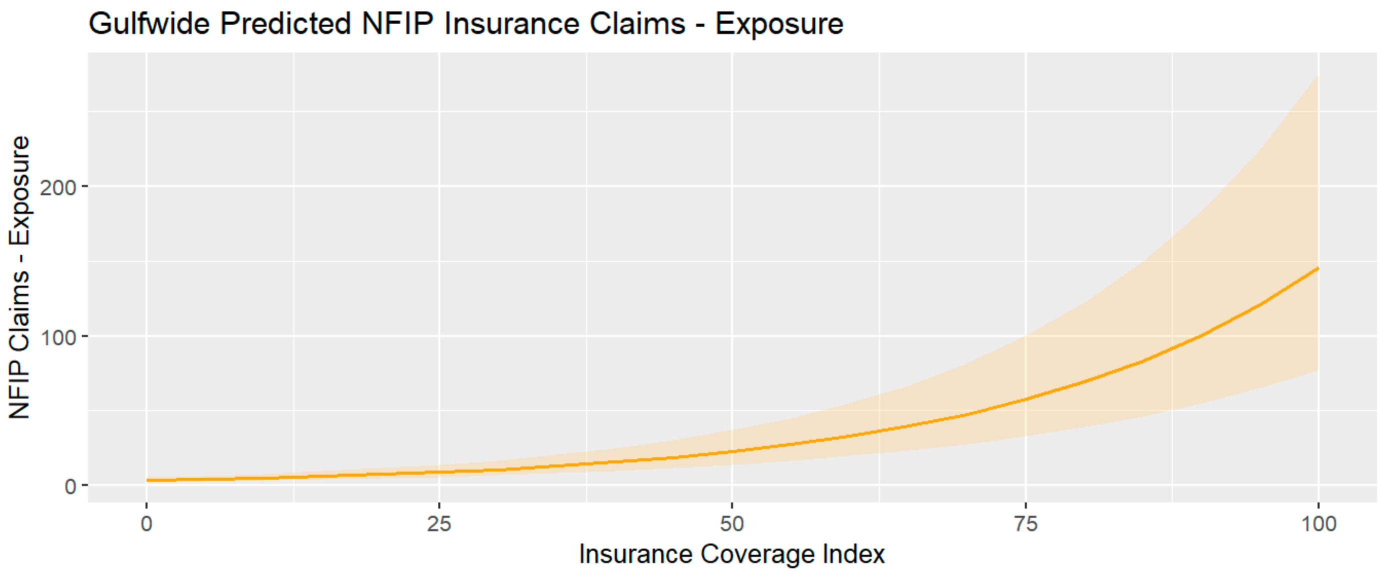

Figure 5. Predicted exposure (NFIP claims) versus insurance coverage index. This Figure depicts the estimated effects of the insurance coverage index on the Gulf-wide exposure (NFIP claims) model using the ggeffects (Ludecke et al., 2024) package.

Regarding our social vulnerability predictors, we find mixed results, with coverage and exposure correlated positively with income but negatively with renters. Regarding renters, various explanations may exist that merit further examination. Renters may live in older areas, rental properties may be relatively underinsured, and renters may live in areas with fewer amenities, such as being close to water. We did not observe any statistically significant correlation with Hispanic communities, but in our models' tracts, a greater proportion of African American residents were associated with less coverage and greater exposure (see Figure 6—Coverage and exposure for pct Black at the tract level). This observation merits further examination but echoes studies of risk [13,16] and may stem from historical housing market disadvantage due to past discriminatory practices, current patterns of segregation, and economic inequality.

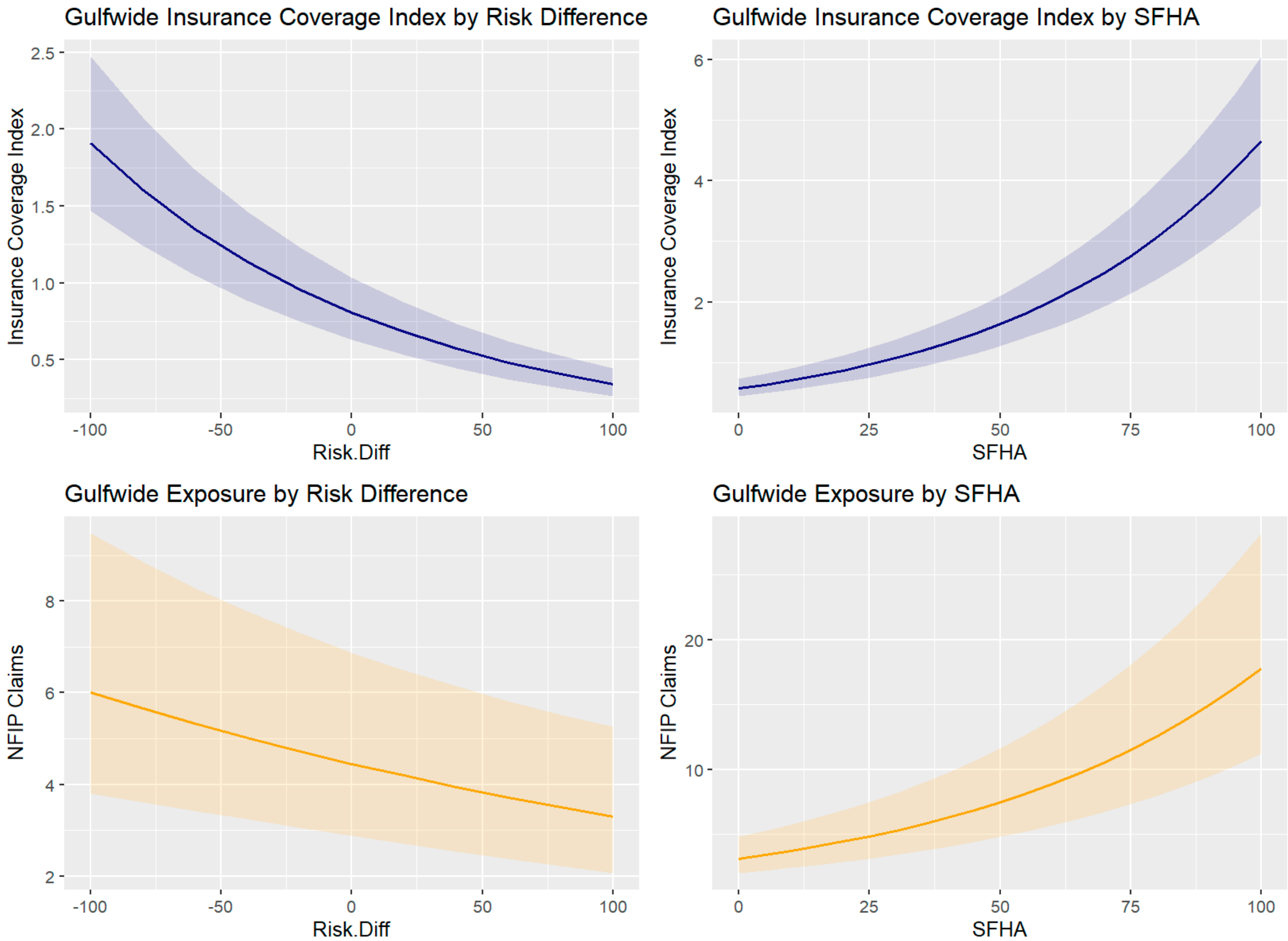

Figure 6. SFHA versus "Risk Difference" in coverage versus exposure models. This Figure depicts claims and exposure in tracts with a greater proportion of homes in the SFHA and also the independent effect of "Risk Difference", implying areas with underestimated risk (F.F. > SFHA) have greater coverage and exposure. This suggests some adaptation to non-SFHA flood risk but also greater exposure for those locations. These findings buttress observations that SFHA-based risk measures may under-communicate the severity of flood risk. Whether the amount of adaptation via insurance is concomitant to increased risk and exposure is something that requires further investigation. We plot these estimates using the ggeffects [33] package.

Finally, this study has potential limitations due to the nature of the NFIP data used and could be extended in the future with a more detailed analysis of heterogeneity by CZ and county. Another question for future research is a more in-depth study of the interaction of "risk difference" and social vulnerability and how this interacts with questions of adverse selection and heterogeneity in community resilience. Our findings are somewhat limited due to their focus on one 10-year period, which may underestimate long-term exposure probabilities in some areas (e.g., Florida, which saw major storms after our study period ended), and a track-level rather than a parcel-level focus. However, longer-term historical exposure estimates are not available at very granular scales. We note that the dip in coverage in the second period of our study may relate to NIFP reforms in 2014 and increasing premiums. We suggest that creating longer-term longitudinal datasets estimating parcel and structure level exposure would be beneficial in further comparing risk-based studies (e.g., Wing et al., 2020) to exposure patterns. Furthermore, the coverage and exposure estimates are admittedly subject to some imprecision given the fact that the coverage estimate is calculated as a directional index due to the complexities of how redacted NFIP contracts are published. Future studies may develop better methodologies for translating redacted policy data into coverage estimates. However, the combination and use of these datasets in a larger regional exposure study is novel. See Figure 7.

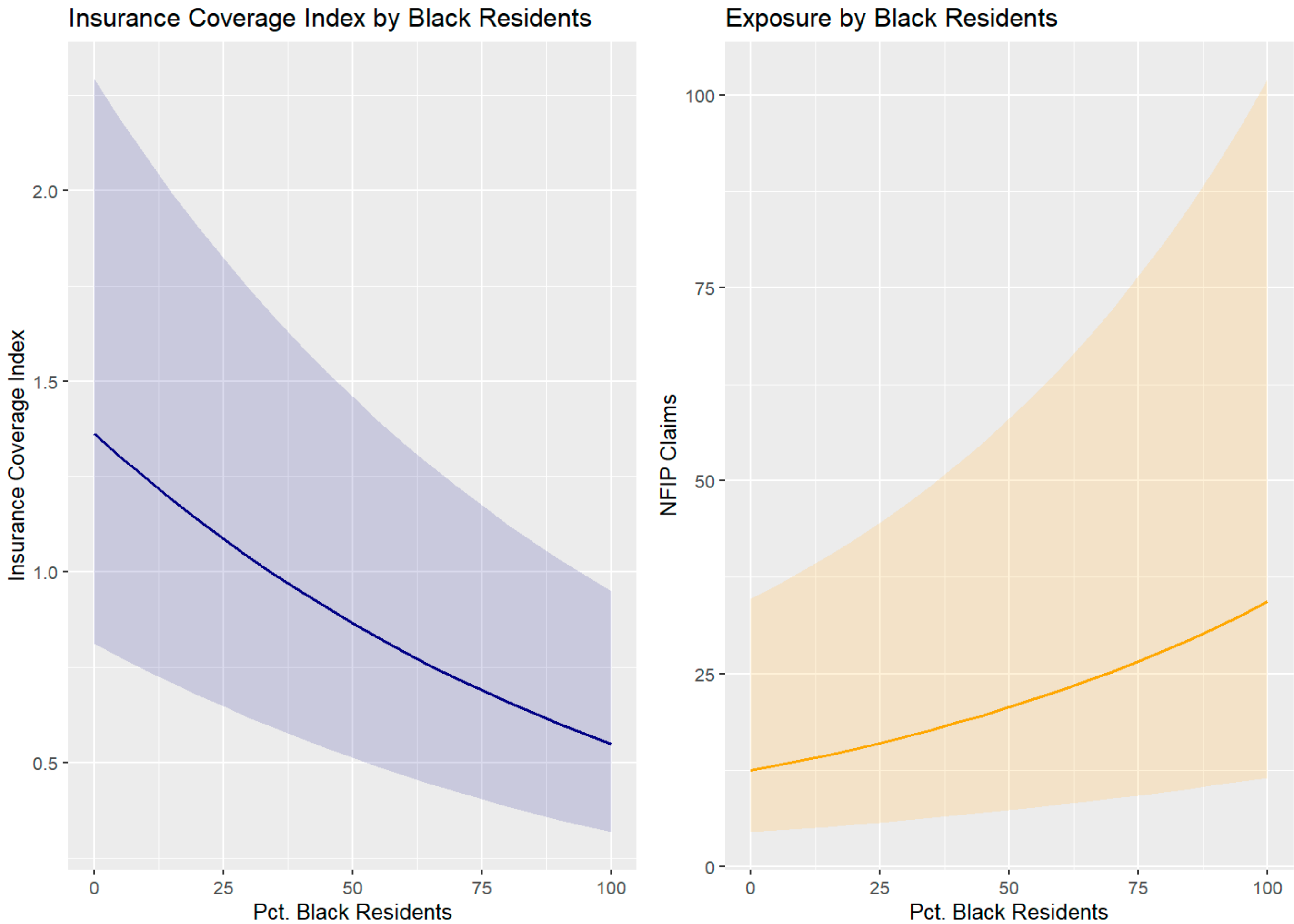

Figure 7. Coverage and exposure for pct Black at the tract level. This diagram depicts the models' estimates of decreasing insurance coverage and increasing flood exposure in our Exposed Counties insurance coverage index and Exposed Counties Exposure (NFIP) models. We plot these estimates using the ggeffects [33] package.

5. Conclusions

We present a modeling technique meant to serve as a basis for research on the effects of recovery and resilience based on modeled estimates of insurance coverage and exposure. We make novel use of NFIP data to consider the intersecting vulnerabilities of insurance coverage, social factors, risk, and exposure at a neighborhood level. This study has been able to replicate many of the findings of risk-based studies of social vulnerability and "risk differences" using measures of observed exposure. Certain communities are socially vulnerable and less economically resilient to hazards [5,34,35], potentially due to disparate access to insurance markets and traditional relief programs [36]. These patterns of differentiated risk and exposure urge refined assessments for future planning and mitigation. Additionally, an understanding of the social dynamics of NFIP uptake and its relationship to flood exposure can strengthen planning in the southeast region. We note that the findings suggest that African American communities in the Gulf Region may be particularly vulnerable to future flooding due to lower rates of NFIP coverage and greater exposure. This may be particularly an issue in more suburban and rural settings. Our findings also show the correlation between exposure and insurance markets, which helps to explain both the need and challenges faced by the NFIP. Risk and coastal status are major drivers of NFIP claims, but there are also social dimensions, which may or may not translate to differences in the built environment differentiated by social dimensions. The exposure model also suggests that broader risk measures for communities than just the SFHA may be necessary to resolve information asymmetries related to flood risk in insurance and housing markets.

Our results also suggest that there is a need to think about flooding and insurance challenges at the community and regional level in terms of focusing on strategies for risk management and resilient development in counties with a high probability of exposure, such as low-lying coastal counties and more inland places with high flood exposure probabilities. But within these communities, newer construction and social factors related to race and income also appear to be important drivers of vulnerability, albeit weaker predictors of exposure than risk measures. The landscape and larger national patterns of development provide the canvas for flood exposure, but community and built environment characteristics provide the nuances previously described by other studies. These might also be associated with state and local policy, but this study does not address local management and the Community Rating Program. Doing so would require a larger longitudinal inventory of state and local policies.

Our findings show a need for greater research on the potential effects of community-level insurance coverage heterogeneity on resilience and recovery after hazard exposure [9]. The results provide a foundation to describe the intersection of growth patterns in the Gulf South and environmental exposure and how these interact with challenges to disaster insurance and resilience. In doing so, this study has innovated in terms of the incorporation of longitudinal exposure and coverage data from FEMA. Furthermore, to address the regional insurance crisis in various Gulf of Mexico states, a future extension would be to model the compounding risk of wind and tropical storm exposure, but the private nature of non-flood related disaster insurance renders data less available for a similar longitudinal study.

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Data Availability Statement: To replicate our analysis and access the data used, please access the supporting data files available at the project GitHub repository of the Douthat Environmental Policy and Governance Lab and LA-SEER Center: https://github.com/LSU-EPG/-Insurance-Coverage-and-Flood-Exposure-in-the-Gulf-of-Mexico.

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Appendix A

Table A1. Summary statistics for "Exposed Counties" models.

Characteristic	N	Mean (SD)	Median (IQR)
Insurance Claims	1325	73 (178)	13 (49)
Insurance Coverage	1325.0	5.0 (5.4)	3.4 (5.9)
Vulnerability: Median Household Income	1325	54,318 (23,875)	49,893 (25,317)
Vulnerability: % Black Population	1325	25 (25)	17 (29)
Vulnerability: % Hispanic Population	1325	9 (12)	5 (7)
Vulnerability: % Renter Occupied	1325	32 (17)	29 (25)
Risk: SFHA	1325	20 (23)	12 (28)
Risk: Risk Difference	1325	−13 (29)	−7 (19)
Urban Form: Median House Age			
Before 1950	9 (0.7%)	9 (0.7%)	9 (0.7%)
1950–1969	205 (15%)	205 (15%)	205 (15%)
1970–1989	625 (47%)	625 (47%)	625 (47%)
After 89	486 (37%)	486 (37%)	486 (37%)
Urban Form: Density Category			
Moderate and High Density (Suburban and Urban)	245 (18%)	245 (18%)	245 (18%)
Low Density (Suburban)	461 (35%)	461 (35%)	461 (35%)
Very Low Density (Rural)	619 (47%)	619 (47%)	619 (47%)
Urban Form: Shoreline County	808 (61%)	808 (61%)	808 (61%)

Table A2. Summary statistics Gulf-wide and exposed.

Characteristic	N	Mean (SD)	Median (IQR)	N	Mean (SD)	Median (IQR)
Insurance Claims	8110	33 (110)	4 (18)	1325	73 (178)	13 (49)
Insurance Coverage	8110	7 (10)	3 (8)	1325.0	5.0 (5.4)	3.4 (5.9)
Vulnerability: Median Household Income	8110	54,362 (25,380)	49,037 (26,922)	1325	54,318 (23,875)	49,893 (25,317)
Vulnerability: % Black Population	8110	18 (24)	8 (22)	1325	25 (25)	17 (29)
Vulnerability: % Hispanic Population	8110	22 (25)	12 (25)	1325	9 (12)	5 (7)
Vulnerability: % Renter Occupied	8110	34 (20)	30 (27)	1325	32 (17)	29 (25)
Risk: SFHA	8110	23 (29)	10 (31)	1325	20 (23)	12 (28)
Risk: Risk Difference	8110	−16 (31)	−7 (21)	1325	−13 (29)	−7 (19)
Urban Form: Median House Age						
Before 1950	247 (3.0%)	247 (3.0%)	247 (3.0%)	9 (0.7%)	9 (0.7%)	9 (0.7%)
1950–1969	1484 (18%)	1484 (18%)	1484 (18%)	205 (15%)	205 (15%)	205 (15%)
1970–1989	4162 (51%)	4162 (51%)	4162 (51%)	625 (47%)	625 (47%)	625 (47%)
After 89	2217 (27%)	2217 (27%)	2217 (27%)	486 (37%)	486 (37%)	486 (37%)
Urban Form: Density Category						
Low Density (Suburban)	2249 (28%)	2249 (28%)	2249 (28%)	461 (35%)	461 (35%)	461 (35%)
Moderate and High Density (Suburban and Urban)	3665 (45%)	3665 (45%)	3665 (45%)	245 (18%)	245 (18%)	245 (18%)
Very Low Density (Rural)	2196 (27%)	2196 (27%)	2196 (27%)	619 (47%)	619 (47%)	619 (47%)
Urban Form: Shoreline County				808 (61%)	808 (61%)	808 (61%)
0	1150 (14%)	1150 (14%)	1150 (14%)			
1	6960 (86%)	6960 (86%)	6960 (86%)			

Table A3. Summary statistics Gulf-wide models by time period.

Characteristic	**N**	**Mean (SD)**	**Median (IQR)**	**N**	**Mean (SD)**	**Median (IQR)**
Response: Claims	4058	13 (70)	2 (7)	4052	53 (136)	10 (37)
NFIP: Insurance Coverage	4058	9 (13)	4 (10)	4052.0	5.6 (7.2)	3.0 (6.5)
Vulnerability: Median Household Income	4058	52,057 (23,942)	47,117 (25,223)	4052	56,671 (26,547)	51,114 (28,338)
Vulnerability: % Black Population	4058	18 (24)	8 (22)	4052	18 (23)	9 (22)
Vulnerability: % Hispanic Population	4058	21 (24)	12 (24)	4052	23 (25)	13 (26)
Vulnerability: % Renter Occupied	4058	33 (20)	29 (27)	4052	35 (20)	32 (27)
Risk: SFHA	4058	23 (29)	10 (31)	4052	23 (29)	10 (31)
Risk: Risk Difference	4058	−16 (31)	−7 (21)	4052	−15 (31)	−7 (21)
Urban Form: Median House Age						
Before 1950	123 (3.0%)	123 (3.0%)	123 (3.0%)	124 (3.1%)	124 (3.1%)	124 (3.1%)
1950–1969	781 (19%)	781 (19%)	781 (19%)	703 (17%)	703 (17%)	703 (17%)
1970–1989	2128 (52%)	2128 (52%)	2128 (52%)	2034 (50%)	2034 (50%)	2034 (50%)
After 89	1026 (25%)	1026 (25%)	1026 (25%)	1191 (29%)	1191 (29%)	1191 (29%)
Urban Form: Density Category						
Low Density (Suburban)	1131 (28%)	1131 (28%)	1131 (28%)	1118 (28%)	1118 (28%)	1118 (28%)
Moderate and High Density (Suburban and Urban)	1803 (44%)	1803 (44%)	1803 (44%)	1862 (46%)	1862 (46%)	1862 (46%)
Very Low Density (Rural)	1124 (28%)	1124 (28%)	1124 (28%)	1072 (26%)	1072 (26%)	1072 (26%)

Table A4. Summary statistics for "Exposed Counties" time period.

Characteristic	**N**	**Mean (SD)**	**Median (IQR)**	**N**	**Mean (SD)**	**Median (IQR)**
Response: Claims	664	42 (159)	6 (20)	661	105 (190)	27 (104)
NFIP: Insurance Coverage	664.0	5.6 (6.2)	3.8 (6.3)			
Vulnerability: Median Household Income	664	52,390 (22,418)	48,817 (24,106)	661	56,254 (25,123)	51,460 (26,166)
Vulnerability: % Black Population	664	24 (25)	16 (29)	661	25 (25)	17 (29)
Vulnerability: % Hispanic Population	664	9 (11)	5 (7)	661	10 (12)	6 (8)
Vulnerability: % Renter Occupied	664	31 (17)	27 (24)	661	33 (17)	29 (25)
Risk: SFHA	664	20 (23)	12 (28)	661	20 (23)	12 (28)
Risk: Risk Difference	664	−13 (29)	−7 (19)	661	−13 (29)	−7 (19)
Urban Form: Median House Age						
Before 1950	6 (0.9%)	6 (0.9%)	6 (0.9%)	3 (0.5%)	3 (0.5%)	3 (0.5%)
1950–1969	109 (16%)	109 (16%)	109 (16%)	96 (15%)	96 (15%)	96 (15%)
1970–1989	332 (50%)	332 (50%)	332 (50%)	293 (44%)	293 (44%)	293 (44%)
After 89	217 (33%)	217 (33%)	217 (33%)	269 (41%)	269 (41%)	269 (41%)
Urban Form: Density Category						
Moderate and High Density (Suburban and Urban)	119 (18%)	119 (18%)	119 (18%)	126 (19%)	126 (19%)	126 (19%)
Low Density (Suburban)	229 (34%)	229 (34%)	229 (34%)	232 (35%)	232 (35%)	232 (35%)
Very Low Density (Rural)	316 (48%)	316 (48%)	316 (48%)	303 (46%)	303 (46%)	303 (46%)

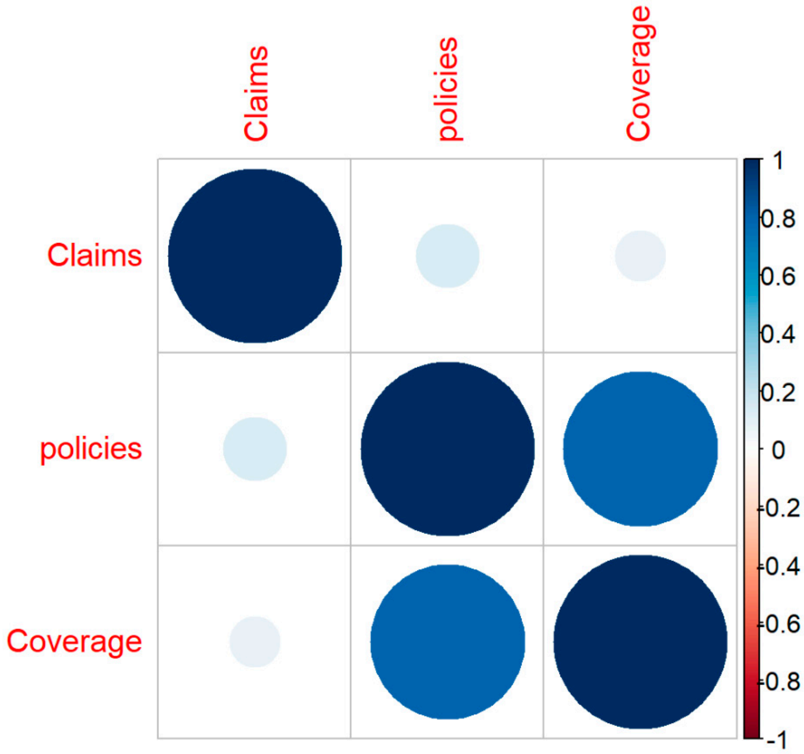

Figure A1. Correlation matrix between NFIP claims, estimated NFIP policy count, and estimated NFIP insurance coverage.

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