PREPARING FOR THE PERFECT STORM: PROPERTY MARKETS AS EVIDENCE FOR COMMUNITY (UN)AWARENESS OF THE COMPOUND RISK OF CLIMATE CHANGE AND HAZARDOUS SITES

by

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(Under the Direction of Susana Ferreira)

ABSTRACT

As climate change fuels more severe and frequent storms, floods, and fires, the risk grows that these phenomena mobilize contamination from hazardous waste and materials sites. Research shows that demographically more vulnerable communities live nearer hazardous sites and in areas of higher risk from climate change. When severe weather releases harmful substances from hazardous sites, the result is a compound disaster event whose whole is greater than the sum of its parts. Using two markets for housing in Glynn County, GA as an indicator of residents' awareness of this compound risk, I find that the main property market capitalizes the contamination and climate change risks and to some degree the compound risk of climate and contamination. The property market on the barrier islands capitalizes only the climate risk. The results of this work make possible community information provision to correct this market failure.

INDEX WORDS: climate change, contamination, risk, property market, market failure

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1. Introduction

Climate change creates an incredibly complex risk landscape for communities across America- in addition to threats of damage to physical infrastructure from fires, flooding, and storms there are also health risks from extreme heat and cold. The interaction between damaged physical infrastructure and increases in human needs for public services post-disaster creates another, additional risk which is greater than the sum of its parts. One such compound risk which has been receiving growing attention is the interaction of climate change and hazardous sites (Gómez 2019, Hasemyer et al. 2020). This compound risk is actualized when severe weather related to climate change causes the release of harmful substances from these sites- something that has been documented in the case of tornadoes, wildfires, flooding and storm surge, and sea level rise (Hasemyer et al. 2020, Brooker and Jenkins 2021, White and Coyne 2022). In a post-disaster situation this actualized risk requires communities to balance responses to infrastructure damage with human health risks to rescue workers and residents. An essential part of preparing for this compound disaster scenario is to understand the extent to which at-risk communities perceive their risk. For example, if residents are not aware that a flood may have mobilized toxic chemicals into their homes, without an information intervention they will likely be exposed to these chemicals and risk health impacts. The goal of this research was to understand this compound risk in Glynn County, GA and whether it is perceived by residents there.

The environmental justice movement motivated research demonstrating that minority and lower-income communities bear a disproportionate burden of hazardous sites in America (United States. General Accounting Office 1983, Chavis and Lee 1987, Mohai et al. 2009). The burgeoning climate justice movement has demonstrated that these same populations are at increased risk from climate change (Islam and Winkel, Singer 2018). Do lower-income, majority non-white communities in America therefore face a "perfect storm" risk landscape where they are at higher risk from hazardous sites and climate change at baseline, facing a compound risk of climate impacts to hazardous sites, and less resilient to that compound risk due to socioeconomic constraints? Using the housing market as a representation of public awareness, this research demonstrates that residents of Glynn County do not have a full understanding of the compound risk of climate change and contamination. Given that it is exceptionally difficult to plan for compound disaster events, and that these kinds of disasters are under-studied, it is of paramount importance that community leaders to raise awareness of compound risks and motivate resilience planning (Zscheischler et al. 2018, Kruczkiewicz et al. 2021). The tool used to make this determination was a hedonic pricing model of property sales in Glynn County. This method relates the sale price of homes to an environmental attribute. The logic is that, if people are aware that a property is at greater compound risk, then they will be willing to pay a lower price for that home (nobody wants to live somewhere that could get contaminated in the next flood!) If people perceive this risk on a large scale (across individuals and over time) then properties with higher compound risk will have depressed sale values compared to less-risky properties. This allows me to test for awareness of the compound risk- by looking for price responses of properties to the risk. While hedonic pricing models of property sales are a common tool in environmental economics research, the unique value of the current work is in the focus on compound risk of contamination under climate impacts, and whether housing markets capitalize this compound risk specifically.

Glynn County, GA was selected for this study because of a high concentration of hazardous waste sites and heightened vulnerability to the impacts of climate change. The county is located along the Atlantic coast of Georgia, and its sea level scenarios are 28% higher than global averages (Sweet et al. 2017). Additionally, it has seen an increasing frequency of tropical storms and floods over the past 100 years (NOAA Historical Hurricane Tracks 1851). Glynn County also has stark demographic disparities, with low-income and non-white populations concentrated in the largest city, Brunswick. Brunswick is across an estuary from Sea Island, St. Simon's Island, and Little St. Simon's Island. These islands are famous for being the location of the vacation homes of the nation's rich and famous and a highly coveted upscale tourist destination. Table 1 shows measures of race, education level, and poverty in Glynn County as a whole, as well as in the City of Brunswick and the aforementioned islands for comparison. Also shown are the count and density of hazardous sites per square mile, using sites that were active in 2021. From these basic statistics, a clear picture emerges of inequity. Hazardous sites are almost two times more prevalent, per unit area, in Brunswick than on the Islands, and close to four times as densely occurring as in the County as a whole. Brunswick residents are also far more likely to be living below the poverty line and without a high school diploma than their Island-dwelling neighbors. This work focused on the past twenty years of compound risk and response in the county, using data from 2000- 2021. Targeting a fairly recent time period made it more reasonable to expect that the compound risk was salient to residents (see Sections 1.1 and 1.2 below).

1.1. Salience of Climate Risks in the Study Area

The risk of climate change can only be capitalized in the housing market if people are aware of it and find it credible. Studies have shown that how recently a community experienced an impact such as unusual flooding or storm damage, as well as residents' political beliefs about climate change, are important determinants of whether this capitalization occurs (Beltrán et al. 2018, Baldauf et al. 2020). A large majority of Americans began to include climate change in their perception of risk in 1988, at that time concerns were focused on extreme heat and the connection had not yet been made in the public consciousness between a globally increasing temperature and more severe storms, fires, or flooding (Leiserowitz 2005). Survey research in the mid-2000s found flagging concern about climate change, with people who had not personally experienced a climate impact considering the risk to occur too far in the future to elicit strong reactions (Weber 2006). However, by the 2010s stated preference research showed that people in general both associated warmer-than average days with climate change and considered this a compelling enough risk to motivate changes in behavior (Li et al. 2011, Hamilton and Stampone 2013, Egan and Mullin 2012). Additionally, a revealed preference experiment using data from 2006-2012 demonstrated that Americans who experienced tropical storms associated these events with climate change (Lang and Ryder 2016). By 2012, the second Obama presidential campaign had climate change and climate-related increases in various types of natural disasters at the center of their platform (The Obama White House). The last year of the Obama presidency, 2016, was anomalous for severity and frequency of severe weather, including Hurricane Matthew (Smith 2017). That storm devastated the southeastern United States, including Glynn County, GA. Residents of Glynn County, GA can reasonably be expected to have heard about climate change prior to the beginning of the study period (2000). By 2016 they can be expected to have heard about the link between climate change and risk of damage to properties in Glynn County, although their personal assessment of the validity and salience of this risk would vary.

The data used to model climate risks at hazardous sites and sold properties in this study were not publicly available during the entire study period. The climate impacts modeled and the year of original model publication were: wildfire hazard potential (2016, updated 2020), sea level rise (2015, updated 2018), storm surge (2014, updated 2018), hurricane wind speeds (1997, updated 2002, 2017), and annual flood risk (1959, updated regularly to 2018). In all cases only the updated version of each data set is available to the public and was used for analysis. Deprecated data versions had modeling errors and were unsuitable for continued use. With the exception of wind speeds and flood risk, all of these data were originally published in the last quarter of the study period. Prior to the publication of these data, public awareness of climate and compound risks would have been based on generalized reporting and lived experiences. After data publication some residents of Glynn County may have utilized this information to glean localized information on climate and compound risks. Updates to FEMA flood zone maps following anomalous severe hurricane activity have been shown to cause people to update their beliefs about flood risk and property value (Gibbons and Mullins 2020). However, due to the high technical barriers to downloading and opening these data sets (with the exception of NOAA's sea level rise data which was accompanied by an interactive web map), it is unlikely that there was widespread consumption of this information. For this reason, and because I could not access deprecated versions of climate data, I was not able to exploit the publication of new climate data as an information treatment. Therefore, while the climate change risks present in Glynn County from 2000-2021 have remained approximately the same, public awareness of these risks should have increased during this time. This increase in salience over time can be attributed to more frequent individual experiences with severe weather, increased political discourse about climate change and its links to severe weather phenomena beyond extreme heat, and the publication of localized modeling of climate change risks in Glynn County. For this reason, I included indicator variables for all floods, storms, and wildfires that occurred in Glynn County during the study period (*Table 2*) (NOAA Historical Hurricane Tracks 1851, Brakenridge 2021, Parker 2021). Included storms were those whose path intersected or passed within 60 nautical miles of Glynn County. Floods were those detectable via satellite monitoring. There was only one wildfire recorded in the county during the study period. The climate event indicators took a value of zero for sales before the climate event, and one afterwards.

1.2. Salience of Hazardous Sites in the Study Area

There were five categories of hazardous sites, all regulated by the US Environmental Protection Agency (EPA), included in this study. To our knowledge this is the first study of its kind to include multiple categories of hazardous sites in the same analysis, making it far more complete than past works. The inclusion of multiple site types also addresses a potential source of omitted variable bias that was not accounted for in past research. The categories were Brownfields, Emergency Planning and Community Right-to-Know Act 302, 311/312 Reporting (EPCRA), National Pollution Elimination Discharge System permits (NPDES), Superfund, and Toxic Release Inventory (TRI). Early in the project I attempted to include Treatment Storage and Disposal Facilities but ultimately removed them from the dataset because I could not find credible information on dates that sites were active. Federal law mandates that information on these sites be publicly available. However, in reality these data have serious issues with missing information, validity, and access. An important contribution of this project is creating a public-facing and complete inventory of sites with accurate locations, discussed in detail in the

Conclusion. For example, of the 23 Superfund sites in the County, 16 of them have incomplete or missing location data in public EPA data downloads. Upon filing a Freedom of Information Act request for detailed location information on five of the sites for which internet research and aerial surveillance did not yield locations, only four of the requested locations were returned. The fifth Superfund site could not be identified in the records on file with the EPA- although it appears in the public data download of Superfund sites in Glynn County. Another example is the public data download tool for NPDES permits. This tool allows users to filter results by the location of the permits. However, while filtering permits by state was effective, the vast majority of records were missing more detailed location data. If a user filtered the data download tool by County or City, for example, they would be returned only a small fraction of the permits existing in the location as records with null values were dropped. To get a full count of the NPDES permits in Glynn County, the entire state of Georgia had to be downloaded, mapped using a GIS software, and then clipped to Glynn County. In order to gather a reliable set of information on the locations and active dates for the hazardous sites used, approximately 10,000 records of hazardous sites were individually verified. Many of these verifications required use of satellite imagery and historical records.

In preliminary stakeholder meetings with Glynn County residents, people expressed awareness of a few hazardous sites in the area- namely LCP Chemicals, Brunswick Wood Preserving, and the Hercules 009 Landfill. All of these are Superfund National Priorities List (NPL) sites. Particularly well-known among community members was the LCP Chemicals site, which is contaminated with toxins that remain uncontrolled and could damage human health. The Georgia Department of Natural Resources maintains local fishing advisories in Brunswick due to water contamination by mercury (a neurotoxin), and polychlorinated biphenyls (PCBs, a known carcinogen and a risk factor for immune, reproductive, neurological, endocrine, and other problems) from the LCP Chemicals Superfund site. Figures 1-5 and Map 1 (link to interactive version of this map) give summary information on the distribution of hazardous sites in Glynn County across site types and years. In Figures 1-5, there is one observation per site per year that it existed in Glynn County during the study period. In each chart subtitle the number of unique observations (*one per unique site*) and the number of total observations (*one per unique site per year*) are both given. Readers may note the uptick in NPDES permits recorded in Glynn County in 2013. This is the year that Georgia switched from using the Permit Compliance System to the Integrated Compliance Information System to track NPDES permits. With this change, a greater number of permits were logged. There is also an increase in NPDES permits in 2018. Most NPDES permits last for five years, so this would be the time for 2013 permits to be renewed. There is also a gap in recorded Brownfields between 2016 and 2020. During this time, the Brownfields program was moved from the EPA to the Georgia DNR (the last EPA Brownfield was remediated in 2016). The GA DNR record keeping system is different from that of EPA, which is the reason for the gap in active Brownfields sites. In Map 1, the shading in Glynn County shows the Centers for Disease Control and Prevention's Social Vulnerability Index (SVI), where a darker color indicates a census tract with greater vulnerability to disaster events (CDC/ATSDR Social Vulnerability Index). The boundaries of the City of Brunswick and the grouping of St. Simon's, Little St. Simon's, and Sea Islands are also noted on the map. Hazardous sites are most densely clustered within Brunswick, and the panel below magnifies this dense city-center.

Finally, I note that awareness of the compound risk of climate change and contamination from hazardous sites is relatively recent development nationally and I do not expect residents of

Glynn County to have encountered information highlighting this compound risk. In 2012 the Obama administration asked all Environmental Protection Agency (EPA) regional offices to publish plans for addressing climate change threats to Superfund sites (Exec. Order No. 13653 2013). However, under the Trump administration those plans were abandoned (United States. Environmental Protection Agency 2018). In 2019 the Government Accountability Office published an analysis of Superfund site vulnerability to climate change that found about 60% of NPL Superfund sites to be located in areas at risk for flooding, storm surge, sea level rise, and wildfires (Gómez 2019). Finally, in 2020 *Climate Insider* published a series of articles highlighting incidents across the nation in which severe weather driven by climate change had caused the mobilization of contamination into communities (Hasemyer, David et. al. 2020).

2. Data and Methods

2.1. Data on Climate, Contamination, and Compound Risk

Measurement of the compound risk of climate change and contamination at hazardous sites in Glynn County followed the methods described in Ingham 2022. In that paper, I propose a novel methodology for ranking the compound risk at hazardous sites using a Compound Risk Index (CRI). This CRI calculation methodology builds upon previous work on creating risk indices, as well as rankings of hazardous sites by their vulnerability to climate change (Cutter et al. 2008, Cutter et al. 2010, Cutter et al. 2012, Cutter 2016, Gómez 2021). Briefly, the CRI method takes geospatial data on modeled impacts of wildfire, storm surge, sea level rise, flooding, and wind damage and overlays these with the locations of hazardous sites. Then, at each site and for each possible impact a value of zero of one is assigned based on whether the modeled impact passes a defined severity threshold (such as feet of inundation, or intensity of fire). Threshold values represent the severity that could be expected to cause a release of contaminants. This severity indicator is then multiplied by the 50-year localized cumulative probability of the modeled climate impact occurring, as well as an indicator for whether the impact in question would mobilize contamination in the specific media present at the site. (For example, a fire could mobilize contamination that is in a storage site but could not mobilize contamination that is present in groundwater.) When the climate impact could interact with the media at a site the indicator was set to one, and zero otherwise. When the calculation stops at this point, the result is the Total Climate Impact (TCI) at a hazardous site. TCI can range from zero (least risk) to one (most risk). TCI accounts for modeled probability and severity of climate impacts at the level of measurement (in this case per hazardous site). If the TCI is then multiplied by the Centers for Disease Control's Social Vulnerability Index (SVI), the result is the CRI (CDC/ATSDR Social Vulnerability Index). SVI is bounded by zero and one, and ranks census tracts within the county according to a percent rank of fifteen socioeconomic indicators, where the greatest social vulnerability corresponds to the highest rank. Thus, the CRI is the TCI weighted by the inverse of resources available in a community to respond to a compound disaster event. Like TCI, CRI can range from zero (least risk) to five (most risk). CRI is a more comprehensive measure of compound risk because it includes contextualization with community vulnerability, which is not included in TCI. Full details on the modeled climate impacts used for this study, severity threshold values, and probabilities can be found in Appendix B.

These same methods, *i.e.* calculation of TCI and CRI, were applied at the property level to understand the degree of risk from climate change as well as the compound risk and social vulnerability at each property. Because there are no hazardous materials present at properties, the contaminated media interaction term was left out of the property-level calculation of TCI and CRI. When measured at the level of hazardous sites, both TCI and CRI are measures of the compound contamination and climate risk. CRI is a more complete measure of this risk because it includes community vulnerability. When measured at the level of properties, TCI and CRI have a different interpretation. At the property level, TCI is a measure of the climate risk only and CRI is a measure of the climate risk accounting for community vulnerability to that risk.

In addition to measuring TCI and CRI at the property level, I also included indicator variables for climate events in Glynn County during the study period that took a value of one when a property was sold after the event (detailed in Section 1.1, *Table 2*). I also included an interaction term between each of these indicators and the property-level risk of that climate event (i.e. property's wildfire risk level for a wildfire, property's flood risk level for a flood, Category 1 storm surge risk for a tropical storm).The property-level risk to a specific climate impact was measured as the product of severity and probability for the specified climate impact, as detailed in Ingham 2022. These climate event indicators and interactions capture suspected time- and location-varying climate risk perceptions detailed in Section 1.1.

I also measured the count of all hazardous sites within one and two miles of each home sale, as well as the average, minimum, maximum, and standard deviation of CRI and TCI values at those hazardous sites. These measures were also recorded per site type. And, because the NPL Superfund sites were expected to be especially salient, an indicator variable for sales within one mile of a NPL site was also included. This is a great improvement over the more standard measure of property exposure to hazardous sites, which has historically been the distance to the nearest site. Recording the count of sites within a circular search radius gives a far more complete picture of the risk landscape surrounding a property, and testing two search radii allows for analysis of the threshold at which risk might be perceived. The choice of one- and two-mile search distances for hazardous sites is supported by previous research. Toxic Release Inventory (TRI) emissions are found to affect air quality within one mile of the emissions source and Superfund sites within 1.86 miles of a property have been shown to affect sale price (Mastromonaco 2015, Currie et al. 2015).

Available data on Superfund and Brownfield sites had slightly ambiguous information on the dates that sites were active (inactive sites are those that have been remediated and are deemed by the EPA to no longer pose a risk to the community). For Superfund sites that were still active in 2021, the earliest date found mentioning the site as an active location was used as the start date and no end date was assigned. For inactive sites, the earliest date found mentioning the site as active was used for the start date, and the Non-NPL Status Date was used as an end date (Mastromonaco 2014). For those archived sites where no historical record of a start date could be found (n = 2), it was assumed that they came into existence and ceased to exist in the year of their Non-NPL Status Date. These two sites without dates were delisted in 2001 and 2002. For Brownfield sites, sites were considered active after the date of the site's application to the Brownfield program or creation in the Brownfield record system. They were considered inactive after their "cleanup complete" date.

2.2. Data on Property Sales

Property attributes and sales data of single family residences were obtained from the Glynn County Government Open Data portal (Glynn County 2021). These data were available for download as a geodatabase including parcel and building boundaries, point locations of addresses, stand-alone tables of property transactions (from here, called "sales") and building names, and relational classes allowing the joining of the geospatial data to the stand-alone tables. These data were from a computer-assisted mass appraisal system and current to May 27, 2021. All property sales were joined to the geospatial files in order to calculate the incidence of hazardous sites and climate risks near the property being transacted. Sale prices were recorded in nominal dollars, and adjusted to real 2018 dollars using the Glynn County all-transactions housing price index published by the St. Louis FED (Bogin and Larson 2019). In order to avoid measurement bias in results due to properties on the edge of Glynn County, for model specifications using the one-mile search distance to count hazardous sites I removed all properties within one mile of the county border. Likewise, properties within two miles of the border were removed when modeling with the two-mile search radius. For example, a property on the edge of Glynn County could in fact be extremely close to hazardous sites in the neighboring county and have a low sale price as a result. But, because I have no record of the hazardous sites in this neighboring county, in my data the property could appear to have zero hazardous sites nearby.

The property-level data included observable characteristics of each house like year built, number of stories, total heated square feet, number of rooms, bedrooms, full baths, and half baths; and categorical variables describing the architectural style, interior wall and floor material, exterior wall and roof material, and the structure's quality grade. Each property was uniquely identified with a parcel ID number, allowing for the creation of a panel data set of sales over time. The initial set of sales recorded had 39,679 observations. Within these, there were 1,485 duplicate property sales recorded in the dataset where the sale date, price, and parcel ID were all exact matches. Of these, only the first observation of each was kept. There were also 3,203 records where the sale date and parcel ID were exact matches but the recorded sale price was different- all of these observations were removed. After removing duplicate sales, property attribute variables were checked for null and zero values. After dropping 230 records where the year of construction, number of rooms, and/or total heated square footage was null, there remained null values only for the number of bedrooms (null = 20), full baths (null = 9), half baths (null = 7,527), and fireplaces (null = 20,939). In all of these cases, it was assumed that the null value was recorded erroneously and should have been a zero. The contribution of each of these variables to the model was checked (see Appendix Table 2) to ensure that they increased explanatory power. In an effort to remove outliers, sales in the bottom and top 1% of the distribution were dropped from the dataset (396 sales under $8,513 and 396 over $2,680,910, out of 39,670 total sales pre-cleaning). Table 3 shows the effect of trimming duplicates, missing data, and outliers from the dataset. Importantly, Table 3 demonstrates that the removal of the 4,126 suspect observations did not affect the count of hazardous sites, climate risk, social vulnerability, and compound risk (the data cleaning did not skew the primary variables of interest). Appendix Figure 2 shows the slightly skewed but overall normal distribution of the log of sale price after data cleaning.

2.3. Theoretical Model

Hedonic price models recognize that there is not a single price and quantity that clears the market, instead modeling heterogeneous goods whose prices vary by quality attributes. Hedonic models of property sales utilize the relationship between characteristics of a location, property attributes, and property prices to derive the implicit price of environmental qualities (Rosen 1974, Roback 1982, Blomquist et al. 1988). They are based on strong assumptions of competitive market conditions (many buyers and sellers, free entry and exit from the market, perfect information) under which the marginal willingness to pay or willingness to accept for attributes of a good can be recovered. In this framework the choices made by property buyers reflect their holistic internal valuation of the environment surrounding the property. Put simply, the amenities, resources, and community that surround a property are a determinant of its sale price. Or, as a realtor would say, "location, location, location!"

In a simple model where agents derive utility from environmental amenities which are capitalized into property prices, in equilibrium, differences in property prices equalize utility across locations. If this were not true then people would have incentives to relocate in order to reach a higher indifference curve (Ferreira and Moro 2010). If people have full information about the environmental quality near properties and are freely able to relocate this is modeled:

Eq. (1) $$v^k = v(r^k(e), e^k) = c \; \forall k$$

where v is the indirect utility function of a representative individual, r^k are rents on residential properties, and e^k is a vector of environmental qualities in location k, and c is a constant. Utility is decreasing in rents and ambiguous for environmental qualities, depending on whether they are positive or negative. In the context of this work the presence of a compound climate and contamination risk would be a negative environmental quality and associated with decreasing utility.

When a hedonic model's goal is to obtain the implicit price of environmental qualities, the total derivative of (1) (see (2)) can be rearranged (see (3)). In Eq. (3) the ratio of the marginal utility of environmental quality and the marginal utility of income (i.e. the marginal rate of substitution between environmental quality and budget) is equal to the coefficient on environmental quality that is estimated in a hedonic regression.

$$\text{Eq. (2)} \qquad 0 = \frac{dv}{de} = \frac{\delta v}{\delta r}\frac{dr}{de} + \frac{\delta v}{\delta e}$$

$$\text{Eq. (3)} \qquad \frac{\delta v}{\delta e} / \frac{\delta v}{\delta r} = \frac{dr}{de}$$

Note: In Eqs. 2 and 3: The location superindices have been removed for visual clarity.

However, if individuals' utility is not equalized across locations due to violations of the initial assumptions (many buyers and sellers, free entry and exit from the market, perfect information) then the left hand side of Eq. (2) total variation in utility, *dv/de,* will not be equal to zero. Instead, the marginal price of environmental quality is the difference between a residual term *(dv/de)/(δv/δr)* and the hedonic differential (see (4)).

$$\text{Eq. (4)} \qquad \frac{\delta v}{\delta e} / \frac{\delta v}{\delta r} = \frac{dv}{de} / \frac{\delta v}{\delta r} - \frac{dr}{de}$$

If that is the case, the hedonic pricing approach will provide biased estimates of the implicit price of environmental qualities, due to omission of the residual term. If the environmental qualities are not capitalized in markets at all, then $dr/de = 0$, and from equation (4), $\delta v/\delta e = dv/de$.

Because the assumption of perfect information is most likely violated in the study area for climate change risks, contamination risk, and compound risk, I do not attempt to estimate an implicit price of these environmental qualities. Instead, I test for whether these risks are capitalized in the market for housing (that is, does $dr/de = 0$?) with the understanding that the estimated coefficient is probably only a portion of the implicit price of these environmental qualities.

Studies on the effect of hazardous waste or emissions sites on housing prices are plentiful. Hedonic pricing models have been used in many study areas to document a negative impact of these sites on property prices when residents perceive the risk posed by the site (Gayer et al. 2000, Greenstone and Gallagher 2008, Mastromonaco 2015, Schütt 2021). Similarly, evidence shows that home prices rebound after sites are cleaned up (Gamper-Rabindran and Timmins 2013, Mastromonaco 2014, Haninger et al. 2017). Response of housing prices to climate change risks are similarly well-studied, and found to be significant in the case of adequate public information on risk (and belief that the risk is real) (Pope 2008, Bernstein et al. 2019, Baldauf et al. 2020, Gibson and Mullins 2020, Hino and Burke 2020).

The relationship between households and hazardous sites is understood here as a combination of disproportionate siting and residential sorting. Disproportionate siting says that firms locate facilities based on local economic conditions such as inexpensive land, access to cheap labor, and the regulatory landscape. Residential sorting posits that households move based on their willingness and ability to pay for environmental quality and other amenities (Tiebout 1956). Hedonic pricing models rely upon and draw inference for the residential sorting causal pathway, but I acknowledge that this is not the only possible explanation for the distribution of homes and hazardous sites. An example is the case of sticky perceptions, where households may have historically sorted on pollution, but the sorting is not reversed even after the area is cleaned up because it carries a stigma of contamination (Messer et al. 2006, Cameron and McConnaha 2017).

2.4. Empirical Model

Knowing that Glynn County has significant demographic disparities (*Table 1*), the question emerged of whether Glynn County meets the requirement of being a single market for property (remember that the theoretical model requires competitive market conditions; while the assumption of perfect information is likely violated, it is best to ensure that the other assumptions are met in order to minimize bias). Thus, preliminary models were run on mainland Glynn County (excluding St. Simons, Little St. Simons, and Sea Island) and compared to results from these islands. Results (*presented in Appendix Table 1*) showed some significant differences between the property market on the mainland and on the islands. Namely, property sales on the islands showed no response to hazardous sites within one mile, and there was a significant and positive response in home sales prices to a flood on March 17, 2003 that was not estimated in the County as a whole. Interestingly, although the islands account for only 9% of the county's area, they contained over 40% of all property transactions (n= 14,505 on islands and 19,379 on mainland). For all following analysis in this work, these two property markets are considered separately.

I use two main specifications of the hedonic regression model. The first is a regression which has spatial and temporal variation for its identification strategy. The second is a repeat-sales model which, by using property fixed effects, uses only inter-temporal variation for identification. Sample selection bias could be an issue for the repeat-sales model if homes that are sold repeatedly differ in unobservable ways from those that are only sold once. Table 4 gives summary statistics for properties in the basic regression and repeat-sales model datasets. Columns (3) and (6) give the result of a difference in means *t*-test between columns (1) and (2), (4) and (5), respectively. This test shows that on the mainland, single-sale homes sell for less, are older and smaller, face more contamination risk and climate risk, are in more socially vulnerable areas, and face more compound risk. On the islands, the situation is interestingly reversed, with single-sale homes selling for more, being newer and larger. However, the islands are consistent with the mainland in that single-sale homes face greater contamination risk and climate risk, are in more socially vulnerable areas, and experience greater compound risk (although the magnitude of each of these differences is vastly different between the two locations). Seeing these differences in observable variables between single and repeat sales suggests that there may be sample selection between these groups on unobservable characteristics as well. Thus, I keep both the pooled regression and repeat-sales model specified below in my final analysis, looking for similar results between the two models. Additionally, all results from the repeat-sales model are qualified with the note that the model only represents the subsample of properties that are sold multiple times.

2.4.1. Pooled Model

The more general specification with both spatial and temporal variation, (Eq.5), models the hedonic log price function as linear in its attributes. The log of the sale price of a home i, sold at time t, is a function of a constant c, a vector of observable attributes X_{it}, a vector of risk variables R_{it}, and an i.i.d. mean zero disturbance term, ε_{it}.

$$\text{Eq. 5} \qquad ln\, Price_{it} = c + \alpha X_{it} + \beta R_{it} + \varepsilon_{it}$$

Elements in the vector β are the coefficients of interest and measure the effect of climate, contamination, and compound risks on the log of sale price. The vector of risk variables R_{it} includes measures of TCI, SVI, and CRI as well as the number of hazardous sites within a given radius of the property, interactions between the count of sites and TCI and CRI, indicator variables for each of the climate events recorded in Table 2 and the climate event interaction terms described in Section 2.2.

In addition to dummy variables for each year in the study, I also utilize census block indicator variables in X_{it} to control for time-invariant unobservable neighborhood quality that would be expected to correlate with sale price of homes (there are 245 census blocks recorded, an average of 1.75 sq. miles in size). Use of census groupings as a control for neighborhood quality is well-supported by existing literature (Mastromonaco 2014). It is important to understand what kind of potential bias is addressed by the inclusion of these spatial controls. If the incidence of hazardous sites is correlated with unobservable and undesirable neighborhood characteristics then there would be a downward bias on the estimated effect of hazardous sites on property sales. Conversely, if the degree of climate change risk is correlated with unobservable and desirable neighborhood characteristics (climate risks tend to be higher closer to the coast) then there would be an upward (and counter-intuitive) bias on the estimated effect of climate risk on property sales. Table 5 compares the sale price of homes (normalized by square footage), number of hazardous sites, social vulnerability, and climate risks observed in Glynn County per commission district (the areas represented by county commissioners) throughout the study period (census blocks are not shown because they are too numerous). Map 2 shows these commission districts (Glynn County Government 2022). Column (6) in Table 5 reports the Chi^2 value for Bartlett's equal-variances test (*oneway* in Stata). The results in Column (6) underscore the need for spatial controls in the pooled regression model- all of the metrics reported are highly significantly different between commission districts. Table 5 supports the idea that climate risk may be correlated with positive neighborhood unobservables (see TCI at Properties and Normalized Sale Price for Districts One and Two, which contain the coastline). Also supported is the idea that contamination risk may be correlated with negative neighborhood unobservables (see SVI at Property and Number of Sites within One Mile for Districts 4 and 5, which comprise Brunswick).

Controlling for year and census-block level variation in neighborhood quality may not fully address omitted variable bias. To answer this challenge, a repeat-sales model looks only at the response of sale price of a single home to changes in the risk landscape surrounding the home. This model includes property fixed effects, so that all attributes that are not changing over time are dropped from the model. In this repeat-sales model, I consider that the location and compound risk levels of hazardous sites (R_{it}) in relation to property sales (Y_{it}) is as good as random, conditional on the time-invariant unobservable property characteristics A_i and time-variant observed covariates X_{it} (Eq. 6). Empirically, this is modeled as the log price of a house i, sold at time t, is a function of a vector of observable attributes and a constant X_{it}, a vector of risk variables R_{it}, a fixed effect for the date of the sale δ_{it}, an unobserved neighborhood and/or property attribute y_i, and an i.i.d. mean zero disturbance term,ε_{it} (Eq. 7).

Eq. 6 $$E[Y_{0it} \mid A_i, X_i, t, R_{it}] = E[Y_{0it} \mid A_i, X_i, t]$$

Eq. 7 $$lnPrice_{it} = \theta X_i + \lambda R_{it} + \delta_{it} + \gamma_i + u_{it}$$

Here, the coefficients of interest are θ and measure the effect of climate, contamination, and compound risks on the log of sale price at the level of an individual property. This repeat-sales model therefore accounts for the potential bias present in the pooled regression model due to unobservable and time-invariant neighborhood and property characteristics such as aesthetics and property/area character acting as a determinant of price (these are captured by y_i). Note that any observable property characteristics are captured in the term X_{it}. This allows the repeat-sales model to capture price responses to changes in the property itself (such as a remodel that adds a room or changes the architectural style). Any covariates where there is no change over time in the attribute (such as the census block in which the property is located) are automatically dropped from the model due to perfect collinearity. X_{it} again includes dummy variables for year as in the pooled model.

In a model where there is grouping in the measurement of an independent variable which would be expected to cause grouping in the values of the dependent variable, it is appropriate to cluster the standard errors at the level of that grouping. In the case of this work, SVI is measured at the census tract level so it takes on a limited number of values (it is not truly continuous), and is a component of the CRI calculation as well as a regressor in some model specifications. Given that sale price of homes is highly dependent on demographic characteristics of an area such as those captured by the SVI, it is reasonable to expect that prices would cluster around SVI values. There are 72 levels of SVI over time in the panel, more than enough for the Liang and Zeger (1986) (Stata *cluster*) to correct the Moulton issue (Angrist and Pischke 2009). Thus, in the pooled regression model I cluster standard errors by SVI. This same clustering method cannot be employed in the repeat-sales model because SVI (and the delineation of census tracts) are not constant over time. The repeat-sales model removes any time-invariant within-cluster heterogeneity, but does not address temporal within-cluster correlation (Cameron and Miller 2015). Thus, in the repeat-sales model standard errors are clustered by census block, which should reasonably account for any clustered correlation between the demographic makeup of an area surrounding a property and the sale price of the property.

3. Results

3.1. Decay of Effect with Distance

Before moving to the main analysis of this work (the estimation of Eq. (5) and (7)), it was necessary to select the appropriate search distance to use in modeling the relationship between property sales and their surrounding risk landscape. All spatially-dependent attributes in R_{it} were measured using a one- and two-mile search distance. Due to the size of the raw property dataset (80,000+ observations) and limitations in available computing power, these measurements were made with two overlapping and concentric circles around the property centroid. Thus, all risk factors contained within the one-mile search distance are also included in the two-mile search distance. Therefore, one- and two-mile covariates cannot be included in the same model because of collinearity. Tables 6 and 7 report the estimates of β with from Eq. (5) for the primary covariates of interest. Clustered standard errors are given beneath each estimated coefficient. Columns (1) and (3) show results when a one-mile radius around the property is used as the spatial extent of the risk landscape. Columns (2) and (4) report the results when a two-mile radius is used.

On mainland Glynn County there is a clear weakening of the relationship between hazardous sites and the log sale price of homes between the one- and two-mile search distances (*Table 6*). When the TCI or CRI at hazardous sites is zero, an additional hazardous site within a mile of a sale was associated with a -2.3% or -2.4% decrease in price ($p < 0.001$), respectively. In contrast, an additional site within two miles of the sale was associated with a -0.90% or -0.97%

decrease in price ($p < 0.01$), again when TCI and CRI were zero, respectively. That is, the price effect of hazardous sites alone (without any compound risk measure) is significant at both search distances but larger for sites within one mile of the sale. In addition to being larger in magnitude, the relationship between price and sites within one mile had greater statistical significance ($p < 0.001$), compared to the two-mile search ($p < 0.01$). The estimated price effect of a one-point increase in Average TCI or CRI at sites when the count of sites within a mile also increased by one (Site Count*Sites TCI and Site Count*CRI, respectively) were -1.2% and -1.6% ($p < 0.05$ and 0.01). These same estimated price effects at the two-mile search distance were -1.3% and -1.6% ($p < 0.001$). These results for the capitalization of compound risk are near equal in magnitude across the two search distances, although the two-mile search resulted in greater statistical significance. In other words, the estimated effect of the presence of hazardous sites decayed with distance from the property, but the estimated effect of compound risk on sale prices did not show evidence of decay. The coefficients on Average TCI or CRI of Sites alone do not bear interpretation, because they are interaction effects- measures of the impact of the TCI or CRI at hazardous sites when the number of sites equals zero. Results reported in Tables 8, 9, 10, and 11 show the estimated effects of TCI and CRI measured at the property level, a far more useful metric.

For property sales on the islands, the sensitivity of sale prices to hazardous sites and compound risks appears quite different than on the mainland (*Table 7*). Among the measured relationships between hazardous sites and log of sale price, only hazardous sites within two miles in the CRI regression (Column (4)) was significant. The estimated effect was a 0.88% increase in the sale price ($p < 0.05$) when the sires within two miles increased by one- a result which does not make logical sense. The only other significant relationship of note was the interaction between the count of sites and their CRI at the two-mile search distance. A one-point increase in the average CRI of sites within two miles, dependent on an increase in the count of hazardous sites, was associated with a 6.8% decrease in sale price ($p < 0.001$). While the one-mile search distance results for island properties were not significant, their direction and magnitude were generally consistent with those for the two-mile search distance, although the two-mile search distance tended to produce larger estimated effects (compare Columns (1) with (2), (3) with (4)).

Because the contamination risk (count of sites) and compound risk (interaction between TCI or CRI and count of sites) within one mile of property sales appeared to have a stronger effect than within two miles in mainland Glynn County, and the response of sale prices to these risks in the islands property market was generally not significant, remaining analysis utilized the one mile search distance so that results between the two property markets could be compared.

3.2. Pooled Regression Model

The results of the estimation of Eq. (5) can be found in Tables 8 and 9. Table 8 reports the results when all hazardous sites are grouped together for measurement. Table 9 shows results when hazardous sites are measured by type of site. Estimates of each element of β are given with clustered standard errors beneath. Columns (1) and (2) report results where TCI and SVI are included as regressors. Columns (3) and (4) report results where CRI is used as a regressor. Models included either TCI (and its interaction terms) and SVI **or** CRI (and its interaction terms). Because CRI is the product of TCI and SVI they cannot be included in the same model due to collinearity. Coefficients on CRI and its interaction terms are the primary metric of interest, as CRI fully captures the compound contamination and climate risk in the context of community vulnerability. However, it is also helpful to understand how the component parts of CRI (TCI and SVI) contribute to any measured effect of CRI on the log of sale price. I include both versions to investigate whether the more complete measure (CRI) elicits a different response than TCI. All estimations of Eq. (5) and Eq. (7) included the entire set of covariates in X_{it} and R_{it}, but for visual simplicity estimates of the elements of α are not shown (*they are reported for estimation of Eq. (5) in Appendix Table 2*).

When modeling hazardous sites as an aggregate (*Table 8*), the sale price of homes on the mainland decreased by between 2.3 and 2.4% per hazardous site ($p < 0.001$) when TCI or CRI equaled zero at the sites (due to the included interaction term between count of sites and the sites' average TCI or CRI). There was no detectable effect of sites on the log sale price of island homes. Where NPL Superfund sites existed, proximity of a home to these sites had no significant relationship with sale price (there are no NPL sites on the islands). The SVI and TCI at properties were not significantly associated with sale price in either property market. On the mainland, but not the islands, a one-point increase in CRI at the property was associated with a -5.2% ($p < 0.05$) decrease in sale price. Finally, the estimated relationship between sale price and the site-count-dependent compound risk (the interaction term between site count and TCI or CRI) was significant both when using TCI and CRI as metrics but only on the mainland (Columns (1) and (2)). On the mainland, a one-point increase in both TCI at sites and count of sites was associated with a 1.2% decrease in sale price ($p < 0.05$), when using CRI this was a 1.6% ($p < 0.01$) decrease. Note that the specification where compound risk is measured using CRI has a larger estimated effect and statistical significance than when TCI is used, which indicates that CRI is indeed the more complete and superior measure of compound risk.

Modeling hazardous sites by site type (*Table 9*) enlightens the drivers behind the response of sale price to count of sites. Among mainland properties, an estimated price effect was only observed for NPDES permits, EPCRA sites, and Brownfields. These effects were between -2.0%

and -2.6% ($p < 0.05$)) for NPDES, -4.7% and -4.8% ($p < 0.001$) for EPCRA, and -18% for Brownfields ($p < 0.05$). The indicator for a property within one mile of a NPL Superfund site was again not significant. The TCI, SVI, and CRI at properties was not significantly related to sale price in either property market. Finally, for the disaggregated model the only significant estimated relationship between sale price and the site-count-dependent compound risk was that of Brownfields, where increasing compound risk posed by Brownfields specifically was associated with between a 12% and 13% ($p < 0.05$) decrease in sale values. In this specification, the CRI model did not explicitly capture compound risk better than the TCI model.

To conclude reporting of the results from the pooled regression model, I summarize the climate event indicators and their interaction terms. The reported estimated price effects of climate event indicators are for properties where the measured risk of that climate effect at the sold property was equal to zero. In other words, it is the price effect for properties that were unlikely to have been affected, relative to properties that may have been impacted. Note that the interaction terms for Hurricanes Michael and Matthew and the wildfire in March 2021 are omitted from the results (this is also true in the repeat-sales model results in Tables 10 and 11). For the Category 5 storm surge risk and wildfire risk values at properties, there was zero variance in the measured values, making it impossible to estimate an effect. I did test out each model with the Category 4 storm surge risk which did have variation within the sample, but it did not produce any detectable relationship in the interaction term (this check was applied in the repeat-sales models as well with the same results).

The flood on March 17, 2003 had an estimated price effect between 18% and 19% ($p < 0.05$) across all specifications for mainland properties with zero flood risk. For island properties with zero flood risk, the estimated price effect was approximately -17% ($p < 0.05$) across all specifications. For the March 17, 2003 flood the interaction variable on island sales was significant across all specifications. It was estimated at an increase in the sale price between 9.3% and 9.5% ($p < 0.001$) across all specifications. This result means that properties which were at greater risk for flooding saw a differential increase in sales values relative to less-risky homes, where being more likely to have been affected made the property less likely to sell for a decreased amount. Then, in Sept. of 2004 a flood was associated with an estimated positive price effect of between 17% and 19% for less-risky homes in the islands property market ($p < 0.001$ when sites aggregated, $p < 0.01$ when disaggregated). This flood did not produce a statistically significant price effect on the mainland The climate event and property risk interaction terms were not significant for the Sept. 2004 flood in any specification. A Tropical Storm in May 2007 was associated with a positive price effect for mainland zero-risk property sales of between 11% and 22% ($p < 0.05$ when sites aggregated, $p < 0.01$ when disaggregated); there was no significant relationship among island sales or any interaction terms. Finally, the interaction term between a flood in October 2016 and property flood risk was statistically significant. The estimated differential price effect of this flood when the property was at greater risk of flooding was between -36% and -37% ($p < 0.05$) across all specifications.

3.3. Repeat-sales Model

Results of estimation of Eq. (7) can be found in Tables 10 and 11. Again, estimates of each element of θ are given with clustered standard errors beneath (although the level of clustering is different, as described in Section 2.4). Columns (1) and (2) report results with TCI and SVI as regressors, and (3) and (4) report results using CRI as a regressor. Note that observations of a zero estimated effect with a standard error (.) indicate covariates which were time-invariant and therefore dropped from the model in differencing.

Using hazardous sites as an aggregate in the repeat-sales model (*Table 10*), the sale price of homes decreased by between 3.2 and 3.5% per hazardous site ($p < 0.001$) when TCI or CRI equaled zero at the sites. There was no detectable effect of sites on the log sale price of island homes. The repeat-sales model could not estimate the price effect of NPL Superfund sites or TCI at each property, because these values were invariant over time. However, the price effects of CRI and SVI were estimated. No significant relationship was found between sale price and CRI or SVI in either property market. Finally, the estimated relationship between sale price and the site-count-dependent compound risk (the interaction term between site count and TCI or CRI) was not significant in either property market.

Separating hazardous sites by their types (*Table 11*), as in the pooled regression model, elucidates drivers of estimated effects in the repeat-sales model. As with the pooled regression model, only NPDES permits and EPCRA sites (but not Brownfields) drove the negative relationship between hazardous sites and property sales on the mainland, and no site type was significantly related to island sale prices. The estimated effects were approximately -2.6% ($p < 0.01$) for NPDES and between -4.1% and -4.2% ($p < 0.01$) for EPCRA. The point estimate on Brownfields in the repeat-sales model for mainlands was larger than for any other site type (similar to results from the pooled regression model), but it was not close to statistical significance. This is likely due to the relatively low number of observations where a Brownfield appeared or disappeared between sales of the same property (see Section 4.1 for details; briefly, there were only 12 observations of Brownfields and they existed for a small subset of the study years). In the disaggregated repeat-sales model, neither CRI nor SVI at the property level had a significant relationship with sale price. Finally, in the disaggregated specification the estimated relationship between sale price and the site-count-dependent compound risk was significant only for Superfund sites on the mainland. The estimated price effect of an increase in the compound risk posed by Superfund sites was between -22% to -27% ($p < 0.05$) where the CRI specification produced a point estimate of greater magnitude but not significance.

To end this section, as with Section 3.2 above, I summarize the results for the climate event indicators and their interaction terms. In the repeat-sales model, the estimates of positive price effects on mainland property sales of the flood on March 17, 2003 were no longer found to be significant. The estimate of a negative price effect of the March 17, 2003 flood and a positive effect of the flood's interaction term on sale price in the island market were also not observed. Instead, the repeat-sales model identified a significant relationship between mainland property sales and a Sept. 2004 flood, Tropical Storm in May 2007, and flood in Oct. 2016. In the island property market, climate events with a significant relationship with sale price were the Sept. 2004 flood, interaction term of a Tropical Storm in June 2016, and in the disaggregated model a May 2014 flood.

For mainland homes, the effect of a flood on Sept. 14, 2004 on sale prices of less-risky homes was not statistically significant. But, the interaction between that flood and property risk was associated with between a 50% and 52% ($p < 0.05$) increase in sale price as the property's flood risk increased. The estimated effect of the Sept. 14, 2004 flood on island sale prices when homes had zero flood risk was between 18% and 19% ($p < 0.05$ for all but aggregated TCI model where $p < 0.01$). The interaction term for the Sept. 2004 flood was not significant in the islands property market. The Tropical Storm on May 31, 2007 was associated with between a 21% and 22% increase in sale prices for less-risky properties on the mainland ($p < 0.01$) across all specifications, and the interaction term was not significant. The interaction term of a Tropical Storm on June 5, 2013 with property Category 1 storm surge risk was associated with a 131% to

138% ($p < 0.01$) increase in sale price as property storm surge risk increased. Finally, for the mainland property market there was an estimated positive price effect of a flood on Oct. 16, 2016 of between 55% and 57% ($p < 0.05$) across all specifications.

4. Discussion

I begin the Discussion by emphasizing the need for a careful interpretation of estimated price effects given the inclusion of interaction terms across all models. The estimated price effect of the count of hazardous sites applies only when the TCI or CRI at those sites equals zero- it is the effect of the sites alone with no climate or community risk. The estimated price effect of TCI or CRI at hazardous sites should not be interpreted as a stand-alone value. Estimated price effects of interaction terms between count of sites and TCI or CRI should be read as the compound risk faced by a property (TCI and CRI of sites, dependent on the count of sites). To understand the climate or climate and community risk at a property, see the estimated effect of TCI at property or CRI at property, respectively. Finally, the estimated price effects of climate events are the effect when the property in question was sold after the impact occurred but was not at-risk for the climate event. Price effects of the interaction between climate events and property risk values are interpreted as the effect on sale price when the property was sold after the climate event and was at an increasing level of risk for that impact. Additionally, I remind the reader that the repeat-sales model likely suffers from sample selection bias, and that its results, if interpreted strictly, should only be applied to repeat home sales. However, the repeat-sales model also controls for unobservable and time-invariant effects at the narrowest possible level- that of the property. For the purposes of this Discussion, and because results from the estimation of Eq. (5) and (7) were generally in accordance with each other, I will refer to results more broadly without this caveat.

4.1. Price Effect of Hazardous Sites Alone

I can be confident that the price effect of hazardous sites on mainland homes is nonzero and that this effect degrades with distance from the hazardous sites. Across both the pooled and repeat-sales models with site types aggregated I measured a decrease of between 2.3 to 3.5% ($p < 0.001$) in price per hazardous site added within a mile of mainland sales. This estimated effect was driven by NPDES permits and EPCRA sites across all disaggregated model specifications. Looking at the site types individually, the point estimate for the effect of NPDES permits was between -4.1% and -4.9% ($p < 0.05$ pooled model, $p < 0.01$ repeat-sales) for mainland sales across all model specifications. For EPCRA sites the estimates across all specifications ranged from -4.1% to -4.8% ($p < 0.001$ pooled model, $p < 0.01$ repeat-sales). The estimated effect of Brownfields was measured at -18% ($p < 0.5$) but only in the pooled model. Overall, these results clearly indicate that the contamination risk posed by hazardous sites is capitalized by the mainland property market (although I make no judgment on whether the risk is fully or partially capitalized- this would require an evaluation of the possible monetary health costs of the sites). Specifically, the risk posed by NPDES and EPCRA locations is capitalized. On the islands, the property market does not capitalize the risk posed by hazardous sites collectively or by type.

The extremely large negative estimated price effect of Brownfields on sale price of -18% ($p < 0.05$) for mainland homes in the pooled regression is likely due to a combination of factors. Like all hazardous sites included in this study, they are expected to cluster in less desirable areas (current or former business or industrial centers), but this clustering should be controlled by the inclusion of census blocks. Unlike many site types in this study, Brownfields are fairly rare (n=12 unique sites in Glynn County). This rarity may contribute to greater concern and awareness of these sites. It would be very difficult for a resident of Glynn County to accurately describe the location of every TRI site in the County without seeing a map because there are so many of them. In contrast, with only 12 Brownfields in the County it may be easier for residents to remember and mentally map their locations. Another explanation for the large price effect of Brownfields is their perceived risk level. NPDES permits, TRI permits, and EPCRA sites are all monitored by the EPA but permitted to continue their release or storage of hazardous materials. This status as permitted activity may lead residents to consider them to pose a lower risk. In contrast, Superfund sites and Brownfields are both considered unsafe for continued use, closed to the public, and classified by the EPA as in-need of remediation to control potential consequences to human health. Superfund sites, like Brownfields, are rarer than other site types (n=22 unique sites). However, most Superfund sites were originally listed by the EPA for contamination shortly after the passage of the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) in 1980. Of the 22 Superfund sites in Glynn County, only 6 became active during the study period. While the earliest date that a Superfund site in Glynn County was listed with the EPA was 1991, many of the sites were active as industrial polluters as far back as 1920. Because the majority of Superfund sites were over ten years old at the beginning of the study period, they may have diminished in residents' perceived risk. In contrast, the Georgia Legislature did not adopt the Hazardous Site Reuse and Redevelopment Act (Brownfields Act) until 2002 and the first Brownfield was not listed in Glynn County until 2011. Thus, these sites are a much more contemporaneous phenomenon and likely carried recency (availability) bias in residents' perceived risk. Finally, as Brownfields are unfit for continued use, they often manifest as abandoned or empty lots. These may present a greater visual disamenity to residents than other sites which are less conspicuous. The combination of these four factors: rarity, need for remediation, recency bias, and visual disamenity were all likely contributing factors in the large price effect of Brownfields on mainland property sales.

4.2. Price Effect of Climate Risks and Community Vulnerability

Almost across the board, the climate risk and community vulnerability measured at the level of properties was not significantly related to sale price. The exception was the relationship between CRI and sale price for mainland properties, which was measured as a 5.2% decrease in sale price ($p < 0.05$) but only in the aggregated specification of the pooled model (*Table 8*). Since this estimated effect was not statistically significant in any other model specification, it is not considered conclusive.

For a more interesting discussion of the capitalization of climate risks, I address the interpretation of the climate event indicators and their interaction terms. The estimated price effects of climate events and their interaction terms were of a far greater magnitude than those estimated for contamination risk or compound risk. This follows expectations, as events like floods and storms are far more visible and therefore salient than the locations of most hazardous sites (in addition to the effects of recency bias). Additionally, disasters often cause structural damage to properties that would be expected to greatly impact prices and the relative value of undamaged properties. Generally, the islands property market and mainland property market responded very differently to climate events, both in terms of which events were significantly associated with a price effect and the direction and magnitude of the effect. For the simplicity of discussion and robustness of results, I focus on the climate events and their indicators which had significant results in respective property markets across both the pooled and repeat-sales models.

In the mainlands property market, all the observed significant relationships between climate event indicators and sale price of homes were positive. This makes sense, as homes that were not at-risk to the climate event were likely less impacted or damaged and are less likely to be impacted in future. Thus, they become relatively more valuable post-disaster. Across all model specifications for mainland property sales, only the Tropical Storm of May 31, 2007 was significantly associated with a price effect in every case. This estimated effect was between 11% and 22% ($p < 0.05$ pooled, $p < 0.01$ repeat-sales).

In contrast, the islands property market experienced both positive associations between climate events and zero-risk property prices. Across all model specifications in the islands property market, the only consistent significant relationship was a positive estimated price effect between 17% and 19% ($p < 0.001$ pooled, $p < 0.01$ repeat-sales) of the flood on Sept. 14, 2004. A positive estimated price effect for a climate event indicator is interpreted in the same way as for the mainland market: that zero-risk properties become more valuable relative to riskier properties after a climate event.

Departing from a focus on only those climate events that were significant in both models for their respective property markets, I conclude by addressing a less-robust but fascinating pattern.

In the islands property market a positive estimated price effect of the interaction between the March 17, 2003 flood and property risk interaction was observed in the pooled model only. The estimated effect of between 93% and 95% ($p < 0.001$) across all pooled model specifications for the March 17, 2003 flood interaction term was coupled with an overall negative estimated effect of the climate event on zero-risk properties of -17% ($p < 0.05$) in those same specifications. This means that properties with a higher risk of flooding sold for more relative to a reduction in property sale prices after this flood. Additionally, the interaction term of a tropical storm in June 2016 was associated with a 131% to 138% ($p < 0.01$) increase in sale prices for island properties as property risk increased, in the repeat-sales model specifications only. In contrast, the flood in Oct. 2016 had a positive estimated price effect on mainland sales of zero-risk properties of 55% to 57% ($p < 0.05$) in the repeat sales model, while higher-risk properties were associated with an estimated -36 to -37% ($p < 0.05$) decrease in sales price in the pooled model. These results from the mainland property market are more consistent with expectation, where risk of climate impacts is associated with downward pressure on prices and less-risky properties are more valuable.

I cautiously posit that the positive estimated effects of increasing property risk on sale prices of island homes could be observed due to FEMA flood insurance payouts or other disaster relief compensation. Properties that are at greater risk for flooding (which was measured using FEMA flood zones) would be eligible for payouts from the National Flood Insurance Program after a disaster event. Properties damaged in a tropical storm would also be eligible for relief payments. Research has demonstrated that wealthier, more educated Americans (such as those living on St. Simons, Little St. Simons, and Sea Island) are able to utilize FEMA payouts to “bounce back” and even “bounce ahead” with extensive home renovations, an effect that is not accessible to lower-income and less-educated individuals (Howell and Elliott 2019). I theorize that island properties at greater risk of flooding (which likely experienced greater flood damage) were more extensively renovated, updated, and repaired after the flood of March 17, 2003 and tropical storm on June 5, 2016 and therefore differentially sold for higher prices after the disaster. Ideally, I would consider information on whether these properties had flood insurance, but this data was not available at the property level.

Overall, it appears that the property markets in Glynn County do capitalize the climate change risk, although only when climate events make this risk immediate and threatening.

Properties with lower risk from specific climate events tended to see increased prices after those events, although not every climate event during the study period elicited a reaction in the market. Additionally, there is some suggestion that in the islands property market climate events could be a boon for affected properties, which may sell for more than their less-risky counterparts post-disaster. This could possibly be due to property renovations after damages, which increase value. Finally, it is worth noting that the climate events which were associated with price effects in the mainland and islands were not the same, which makes sense given that the two property markets have very different exposure levels to floods, storms, and other climate impacts.

4.3. Price Effect of Compound Risk

Capitalization of the compound risk (indicated by interaction terms between TCI or CRI and count of sites) was inconsistent between model specifications. In the pooled regression model of mainland property markets when sites were aggregated a significant relationship emerged between sale price and compound risk. The estimated effect was -1.2% ($p < 0.05$) and -1.6% ($p < 0.01$) for TCI and CRI respectively. This result would indicate that the compound risk is capitalized and that this capitalization includes a contextualization of the compound risk with social vulnerability (note the greater magnitude and significance of the CRI estimate). In the pooled regression model of the mainland property market where site types were disaggregated, this estimated effect was distilled down to Brownfield sites alone, where an increasing compound risk from these sites was associated with a -12 to -13% decrease in sale price ($p < 0.05$). This large estimated price effect of the compound risk of Brownfields follows naturally from the very large estimated effect of the contamination risk of these sites (-18%, $p < 0.05$). Turning to the repeat-sales model, which more tightly controls for potential omitted variable bias associated with time-invariant unobservables, the relationship between sale price and measures of compound risk was significant only for Superfund sites alone and estimated at -22% to -27%. Here the contextualization of TCI with SVI produced a point estimate of greater magnitude but not significance. The large estimated price effect of the compound risk of Superfund sites is interesting given that the contamination risk alone was not close to significance and had a small estimated coefficient. It suggests that the compound risk of Superfund sites may be more salient than the sites alone, which would align with the theory that recency bias from climate events impacting select high-risk Superfund sites caused concerns among community members that were not felt for sites with zero risk. As mentioned in Section 4.1, the contamination risk of Superfund sites was generally established many years prior to the beginning of the study period, making it less salient, while climate impacts to Superfund sites during the study period may have driven the significant estimated compound risk price response. Finally, the compound risk was not capitalized in any specification for the islands property market.

Overall, this suggests that the estimated relationship between compound risk and sale price is far more tenuous than the one estimated for the contamination risk alone. While significant capitalization of the compound risk was estimated in some cases for the mainland property market, this result was highly sensitive to model specification and sample size. When compared to the more consistent results for the relationship between sale prices and contamination risk alone (count of sites) or climate risk (climate event indicators and interactions), I can neither affirm nor deny that the mainland property market in mainland Glynn County capitalizes the compound risk of contamination, climate, and community vulnerability. I can conclude that the islands property market does not capitalize the compound risk, an unsurprising finding given that it was similarly unresponsive to hazardous sites.

5. Conclusion

In summary, in the mainlands property market of Glynn County, GA there is strong evidence that the contamination risk of hazardous sites is capitalized in the market for property. There is no evidence suggesting that the latent climate risk faced by properties in mainland Glynn County is capitalized. However, results do suggest that consumers of property are aware of climate risks after a climate event has impacted the area and made the risk more apparent. Results do not conclusively demonstrate whether consumers of property in mainland Glynn County are capitalizing the compound risk of contamination, climate, and community vulnerability. When results showed capitalization of the compound risk for mainland property sales, the point estimates indicated a negative price effect of the risk and that this capitalization was contextualized with community vulnerability. However, this result was highly sensitive to model specification and sample size. Given that results for contamination and climate risk were robust across four model specifications, the lack of consistent evidence for compound risk capitalization suggests that this compound risk is not highly salient and is not accounted for by the majority of property consumers.

The islands property market in Glynn County revealed starkly different results. On the islands, the property market does not capitalize the risk posed by hazardous sites collectively or by type. The climate risk is capitalized in much the same way as in the mainland property market, with the interesting exception of the cases where properties at greater risk from flooding increased in value relative to less-risky homes. I posit that this may be due to remodeling undertaken with disaster relief funds or other sources of capital. Finally, there was no suggestion that the compound contamination, climate, and community risk was capitalized at all in the islands property market.

Consumers' (often irrational) economic decisions are not an accurate indicator of their access to information (Ambuehl and Li 2018). However, they are an accurate reflection of individuals' beliefs. Finding no conclusive evidence that the compound risk of climate change and contamination is captured by the housing markets in Glynn County, I can state that consumers of property in the county do not fully perceive this risk. Even as more information has become available on the risks of climate change in the area and contaminated sites, people have underreacted to this information when forming or updating their beliefs.

Knowing that residents perceive the contamination risk alone of hazardous sites near their property, I expect to find that the measured effect of compound risk on property prices is in some cases nonzero (as it is in-part capturing the effect of contamination risk). But, since the impact of a compound disaster event is greater than the sum of its components, the compound risk is greater than the sum of climate and contamination risks alone. This indicates that the measured erosion of property prices related to compound risk is likely an undervaluation of the real monetary risk faced by those properties from this risk. Additionally, fixed effects models are known to be susceptible to attenuation bias due to measurement error in panel data. Knowing that the data on hazardous site locations and active dates are noisy, the estimated effect of these sites should be less than the true effect.

Research on issues of domestic climate justice has received far less attention than international distributions of climate risk (Schlosberg and Collins 2014, Agyeman et al 2016).

Given evidence from previous research, this study aims to motivate improved climate-risk management at hazardous sites through information provision (Wang et al. 2020). Through a collaborative process with community members, I have developed a suite of interactive mapping tools that will be disseminated in Glynn County with special emphasis on at-risk communities in the Brunswick area. Our partner organizations plan to introduce these tools via a community fair, neighborhood planning meetings, and after church services. The tools created are all mobile-friendly because community representatives report that many residents do not have access to computers but do have smartphones. There is a neighborhood search tool that allows users to enter an address or tap a map of Glynn County and generate reports on hazardous sites (and their CRI, TCI, and SVI values) within 2-mile radius of the search location. Our interactive data dashboard displays responsive metrics on the average CRI, TCI, and SVI within the map window. An analysis mapper allows partner organizations to run more advanced statistical analysis on the data created in this study, as well as submit updates to the database. I also developed a citizen science application whereby community members can contribute to a public repository of information of on-the-ground conditions at hazardous sites in Glynn County. Contributors can provide information such as changes in contamination status or an observed climate impact like flooding that could put residents at risk. Ongoing work by the research team is expanding on the questions of Glynn County residents' perception of climate, contamination, and compound risks and their belief updating when presented with interactive and location-specific information on these risks. In this work, residents are surveyed before and after interacting with the mapping tools and citizen science mobile application. Finally, all the data created for this study is publicly available and free to download, and the link to do so has been shared widely with community members and partner organizations. It is my hope that this emphasis on community outreach helps to catalyze real wellbeing improvements for the residents of Glynn County. This work is intended to provide information for local residents as well as policy-makers.

In environmental economics, market failures can be used as warning signs that government intervention may be warranted to create improved efficiency and equity in allocation. In this case, I am studying the allocation of risk among residents of Glynn County. Disclosure of risk information can help correct market failure such as lack of capitalization of climate risk in housing markets and motivate firm-level reductions in toxic emissions (Konar and Cohen 1997, Pope 2008, Lee 2021). A recent study using firms in the TRI database demonstrated that polluting firms are responsive to public disclosure of effluent information. However, they are heterogeneously responsive as a function of business-location socioeconomic status factors so that polluting firms may relocate to marginalized communities in response to information disclosure (Wang et al. 2020). Additionally, there is evidence that regulatory actions against polluting or hazardous sites are correlated with the political power of local communities (Banzhaf et al. 2019). Therefore, attempts to encourage climate justice via public information must not be isolated ("make the information public and justice shall be served") but rather incorporated as a prong of community outreach and empowerment.

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Appendix A: Additional Results

Appendix Table 1 shows the results of initial regression models comparing mainland Glynn County to Glynn County as a whole. The vector of property covariates is excluded from the results for visual clarity.

In Appendix Table 2, I report the full results of the pooled regression model for the two property markets. All covariates are included in both R_{it} and X_{it}, but for visual clarity the climate event indicators and their interaction terms are not reported (they are reported in Table 8 of the main paper). Numerical property attribute covariates are reported here for those interested in their coefficients. Some may note the negative coefficients on the number of rooms, number of bedrooms, and number of half baths are negative. While initially unexpected, this result makes sense when understanding that the inclusion of total heated square feet in the model means that a greater number of rooms (holding square footage constant) results in a smaller square footage per room. Homes with more open floor plans thus have fewer rooms and would be expected to sell for a greater amount. The value of including the number of rooms, bedrooms, bathrooms, and half bathrooms in the regression is supported by the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) scores of models with and without these room count variables included. The AIC and BIC of the mainland aggregated model with TRI (Column (1) in Appendix Table 2) were 1.84561 and -183621.7, respectively. When all room count variables were removed (rooms, bedrooms, full baths, half baths) they were 1.848381 and -183601.8, respectively. I also tested this model with the bathrooms included and the room/bedroom counts removed, wrestling in an AIC and BIC of 1.845686 and -183639.4 just slightly larger than the original model specification. These same tests were run for the islands property market (Column (2) in Appendix Table 2). AIC and BIC were: 1.190404 and -135940.2 for the original, 1.202212 and -135907.2 with no room counts, 1.191074 and -135947.6 with bathrooms included but no other room counts. In all cases, the inclusion of all room count variables is supported.

Appendix B: Details on CRI Calculations

A. Interpretation Cautions

It is important to emphasize that this research uses data on possible future climate change impacts, but as with all future effects there is a high degree of uncertainty. The real climate change impacts to Glynn County could include factors not considered here, and any given natural disaster could have impacts not captured by these data and models. Additionally, much of these data are derived from models and/or probabilistic modeling (not direct observation). While these models attempt to give the best possible picture of the severity and probability of climate change impacts, they are inherently uncertain and should not be used to make definitive statements about what will occur or even which climate change impacts will be the most important in the future.

B. Climate Impact and Probability Data Sources

Wildfire burn intensity and probability data were available from the Southern Group of State Foresters (SGSF). They are available via an online data portal at https://southernwildfirerisk.com/. Sea Level Rise (SLR) probability for this study was from the National Oceanic and Atmospheric Administration (NOAA) 2018 report on SLR scenarios (Sweet 2017). This is different from Ingham 2022, which used the 2022 update to this report. Since the study period ended in 2021, the updated SLR scenarios would be inappropriate to use as residents of Glynn County could not have utilized the updated information in forming their risk perceptions. SLR inundation levels were available from NOAA via an online data portal at https://coast.noaa.gov/slrdata/. Storm surge probabilities for Glynn County were provided by Dr.

Timothy Hall, from his work that is published in Hall et al. 2021. Storm Surge inundation levels were available from NOAA via an online data portal at https://www.nhc.noaa.gov/nationalsurge/. Flood probability and inundation were available from the Federal Emergency Management Agency (FEMA) via an online data portal at https://www.floodmaps.fema.gov/NFHL/status.shtml. Wind damage probability and wind speeds were available from FEMA's HAZUS software available via online data portal at https://www.fema.gov/flood-maps/products-tools/hazus.

C. Climate Event Severity Thresholds

For wildfires, fire intensity was measured as a categorical value ranging from 1 to 5, with 5 classified as "Very High". Categories 1 and 2 were "Lowest Intensity" and "Low", respectively. Category 3 was used as the severity threshold because it was the transition to "Moderate" fire intensity. For sea level rise, a non-zero amount of inundation at a hazardous site was considered a severe climate impact as it could mobilize contamination in aqueous or soil media. For storm surge produced by hurricanes, a non-zero amount of inundation at a hazardous site was considered a severe climate impact as it could mobilize contamination in aqueous or soil media. For flooding, the data available from FEMA contained the Flood Hazard Zone as designated by the agency. Therefore, the flood spatial data already contained what is essentially the product of an indicator variable for inundation and a probability of flooding. Flood Zones with a value of 0 would not be inundated by a 100-year or 500-year flood. Flood Zones with a value of 0.01 would be inundated by a 100-year flood. Flood Zones with a value of 0.002 would be inundated by a 500-year flood. The annual flood probabilities (0.01 and 0.02) were multiplied by 50 to get the 50-year cumulative probability. Finally, for wind damage I used data on probabilistic wind speeds for a 100-year and 500-year return period (available return periods are 10, 20, 50, 100, 500, and 1,000. 100 and 500 year return periods were chosen for consistency with the flood return periods from FEMA). Wind speeds affect structures differently depending on many factors such as building material and architecture. However, the high wind threat range from NOAA begins at 90 mph and is the threshold at which it is considered likely that structural damage will occur (NOAA 2017).

D. Localized Climate Event Probabilities

Burn probability data was available as a data layer in the data download from the Southern Group of State Foresters. Annual burn probabilities were displayed as categorical variables that represented a range of values. The burn probability was kept in its original categories through the process of taking a spatial average. After taking this average value, probabilities were assigned using the rule that if a site's average was less than 0.5 from the category's starting value it would receive the lower bound, and if it was at 0.5 or more away from the starting value it would receive the upper bound probability (ex. Average value is category 3.7, site is assigned the probability at the upper bound of category 3; average value is 3.2, site is assigned the probability at the lower bound of category 3). Annual probabilities were multiplied by 50 to create a cumulative 50-year probability.

The probability of sea level rise (SLR) is particularly difficult to understand because it is directly linked to the rate of accumulation of greenhouse gasses (GHGs) in the atmosphere, and this is influenced by an incredibly complex system including international economics and policy. RCP 8.5 is the emissions scenario that most closely tracks with real emissions to date and appears to be the best matched scenario out to the mid-century (Schwalm et al. 2020).[1] The Global Mean Sea Level Rise (GMSLR) associated with RCP 8.5 is best predicted at 0.5-1.3

[1] The scientific community has criticized RCP 8.5 for some of its 'business as usual' assumptions including continuing rapid growth in coal-fired power plants. The RCPs have now been replaced by Shared Socioeconomic Pathways (SSPs). SSP 5 baseline scenario is analogous to RCP 8.5.

meters by 2100, with 90% confidence (Kopp et al. 2014, 2016; Mengel et al. 2016, Miller et al. 2013, Slangen et al. 2014). Humanity's continuation on the RCP 8.5 emissions path is and an associated 0.5-1.3 meters GMSLR by 2100 is thus taken as given, a necessary assumption in generating a probability for the amount of local SLR produced in Glynn County by this change. Appendix Table 3 shows the local SLR in Glynn that corresponds to each increment of GMSLR, as well as the localized probability of occurrence (Sweet et al. 2017). Because data on the inundation produced by SLR are only available in 1-foot increments, 1ft. of local SLR with a 100% probability was selected for this risk assessment.

The probability of flooding was available with FEMA data download. Currently the FEMA flood risk maps do not account for SLR or global climate change. The FEMA maps simply display the 100- and 500-year flood zones. From these, a 50 year cumulative probability was derived by multiplying the annual probability by 50 (the annual probability is unconditional). Probability of wind speeds was also available with FEMA data download. This wind data considers the overall wind risk to the United States, and was created from 100,000 years of simulated storms. It does not represent actual storms that have or will occur. It represents modeled wind speeds for 100- and 500-year storms. From these, a 50 year cumulative probability was derived by multiplying the annual probability by 50 (the annual probability is unconditional).

Finally, localized hurricane probabilities were derived from data provided by Hall et al. 2021. In this study, mean annual rates were derived for simulated Tropical Storm tracks crossing "gates" defined by a northernmost and southernmost coordinate in the Atlantic Ocean and making landfall in the United States. The simulation used to produce these data did consider the impacts of global climate change on ocean surface temperatures. There were three gates that covered the coastline directly adjacent to Glynn County, GA. The middle of these, most closely matches the Glynn County coastline. However, Tropical Storms can cause damage in a region even if they do not cross the gate directly associated with the region due to storm surge, spatial extent of the wind-field, or impacting the inland region after crossing at a different gate. For this reason, a weighted average was taken of the probabilities across the three nearest gates where the probability at the middle gate was given twice the weight of the others. Additionally, the modeled data available on annual tropical storm probabilities only extended to 2050 and was available in ten-year increments. Therefore, the modeled probabilities for the 2040s were used to represent the 2050s and 2060s in order to extend to the full 50-year cumulative probability. It should be noted that the simulated gates are very small targets compared to the entire Atlantic seaboard. Because of the small target area, projected rates are low, with means derived from only about 1,000,000 simulated years. For the rarest events (Category 5 hurricanes) the simulated means did not converge well. While the uncertainty of these simulated landfall return rates is unknown, they were generally consistent with other empirical findings about the trends in Atlantic Tropical Storm activity.

Appendix B References

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Table 1: Summary of Glynn County, Brunswick, and Islands Demographics and Hazardous Sites

	(1) Glynn County	(2) Brunswick	(3) Islands
Non-white Population	36%	67%	7.1%
Population with less than High School Diploma	8.4%	12%	2.3%
Population in Poverty	18%	33%	4.2%
Hazardous Sites in 2021 (per sq. mile)	265 (0.62)	40 (2.33)	54 (1.40)

Demographic information is from the 2014-2018 American Community Survey (CDC/ATSDR Social Vulnerability Index). Data sources for hazardous sites are listed in Appendix A.

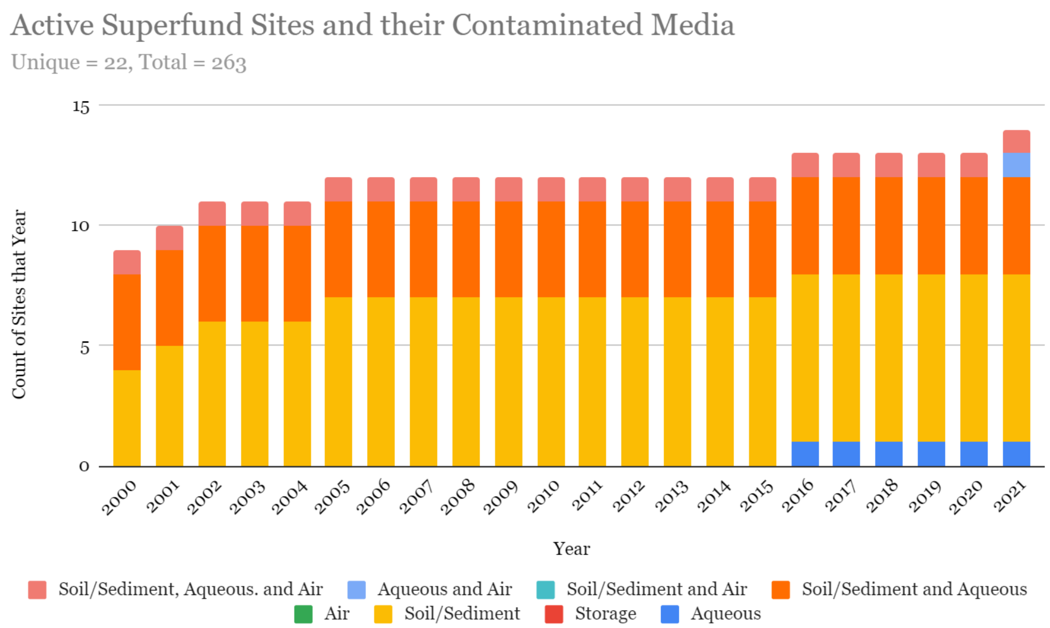


Figure 1: Distribution of Active Superfund sites per year, and the Contaminated Media at these Sites

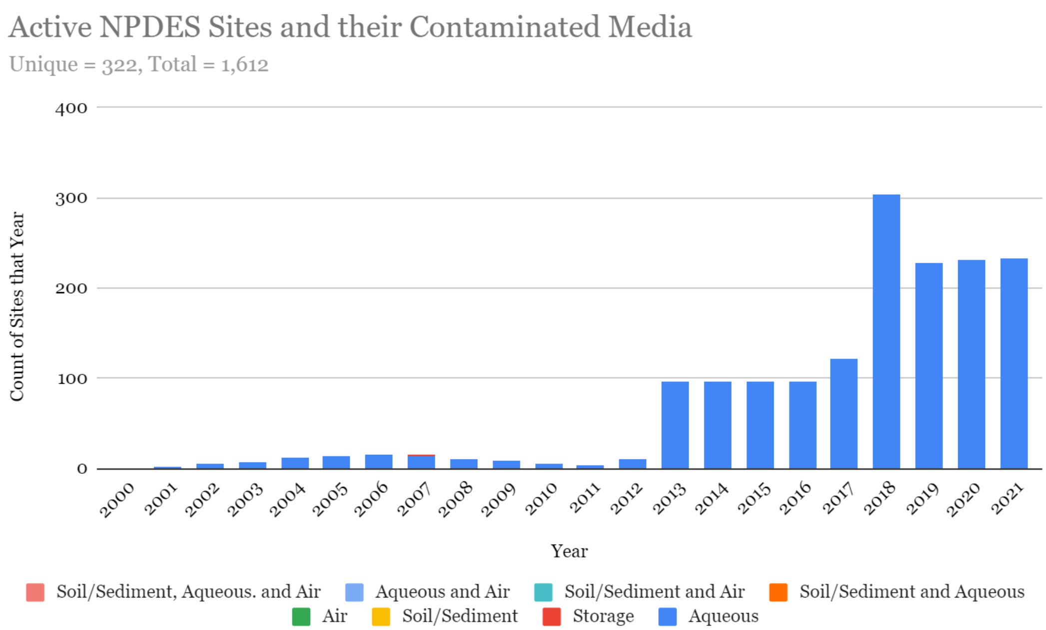


Figure 2: Distribution of Active NPDES sites per year, and the Contaminated Media at these Sites

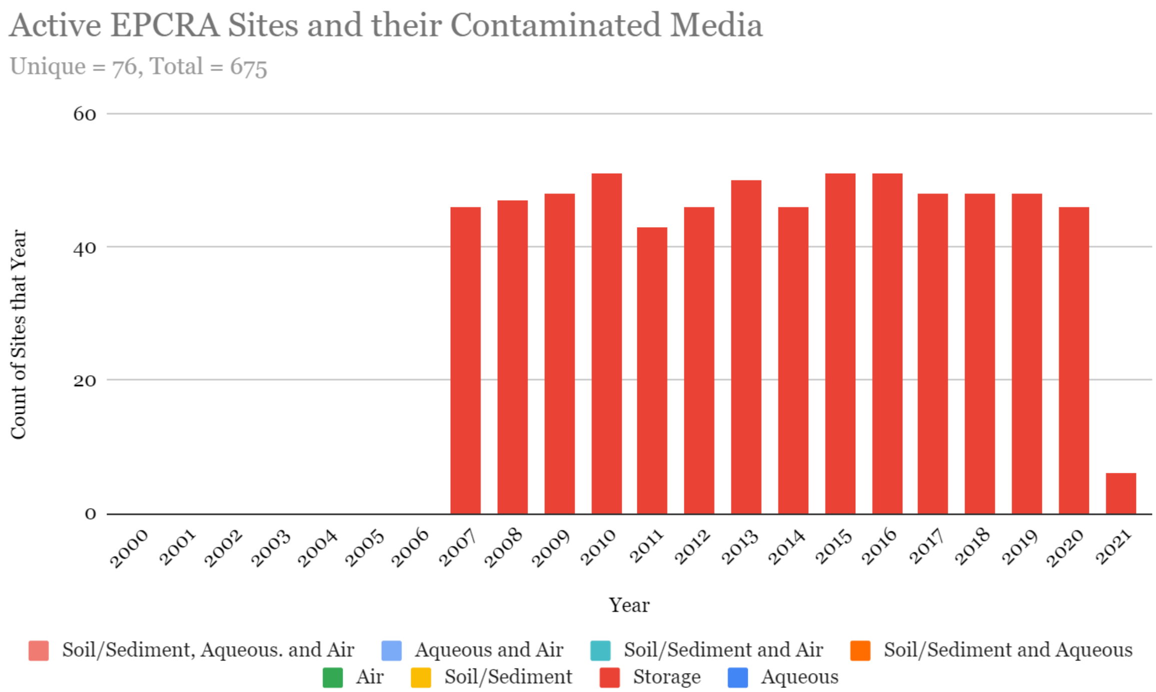


Figure 3: Distribution of Active EPCRA sites per year, and the Contaminated Media at these Sites

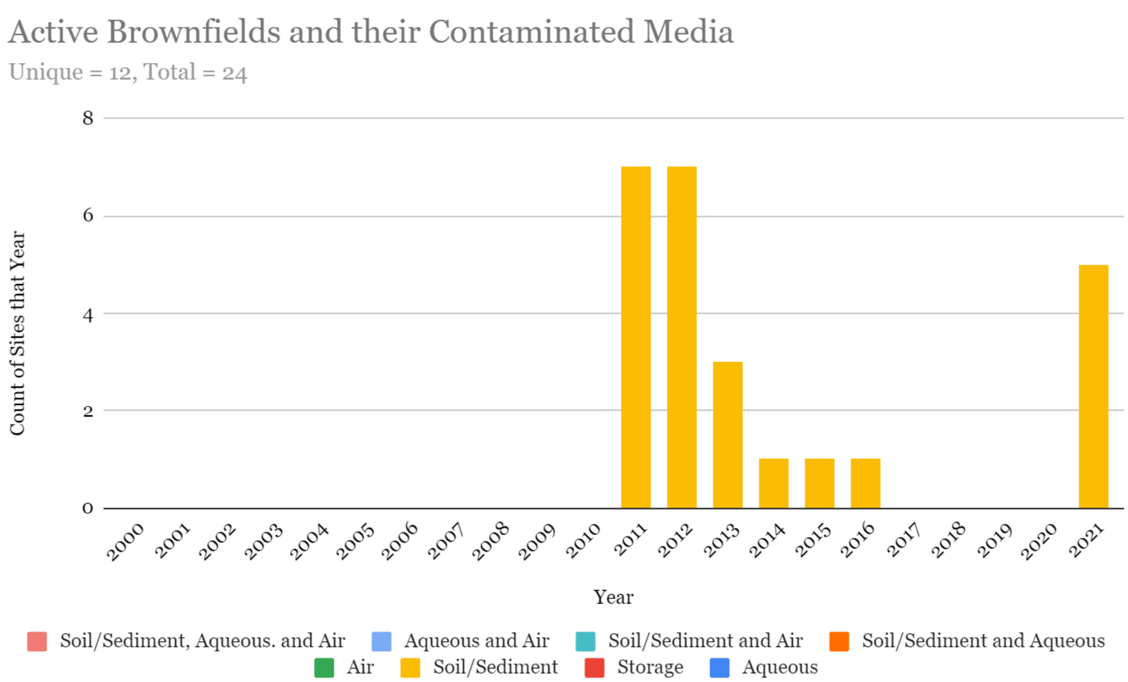


Figure 4: Distribution of Active Brownfield sites per year, and the Contaminated Media at these Sites

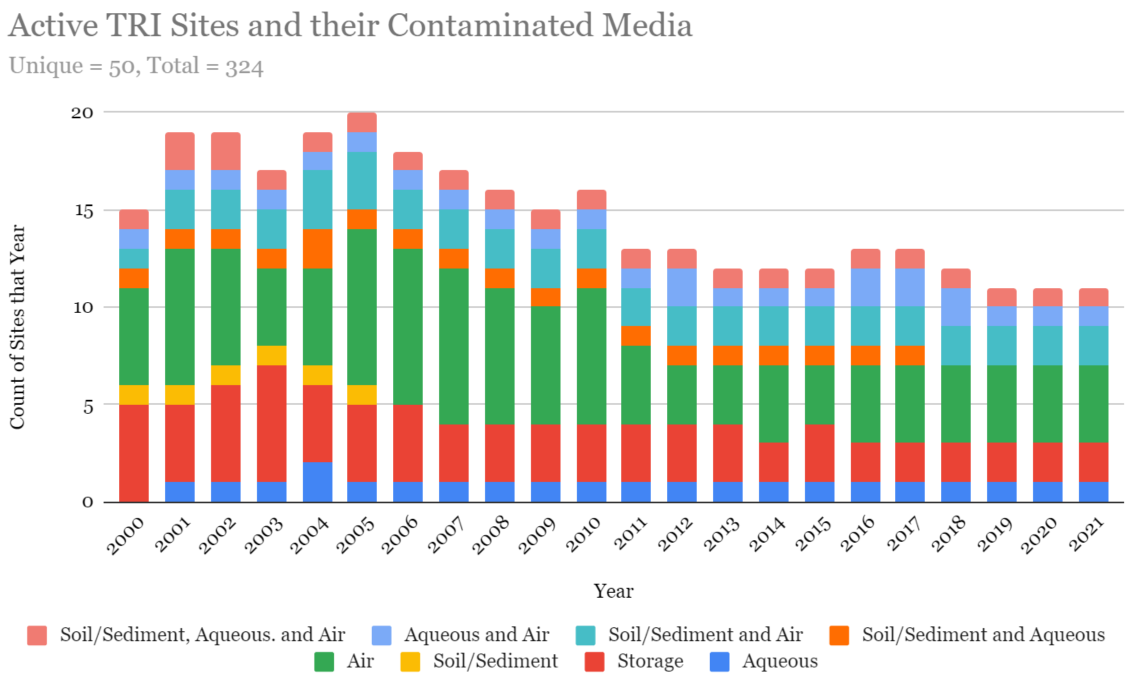
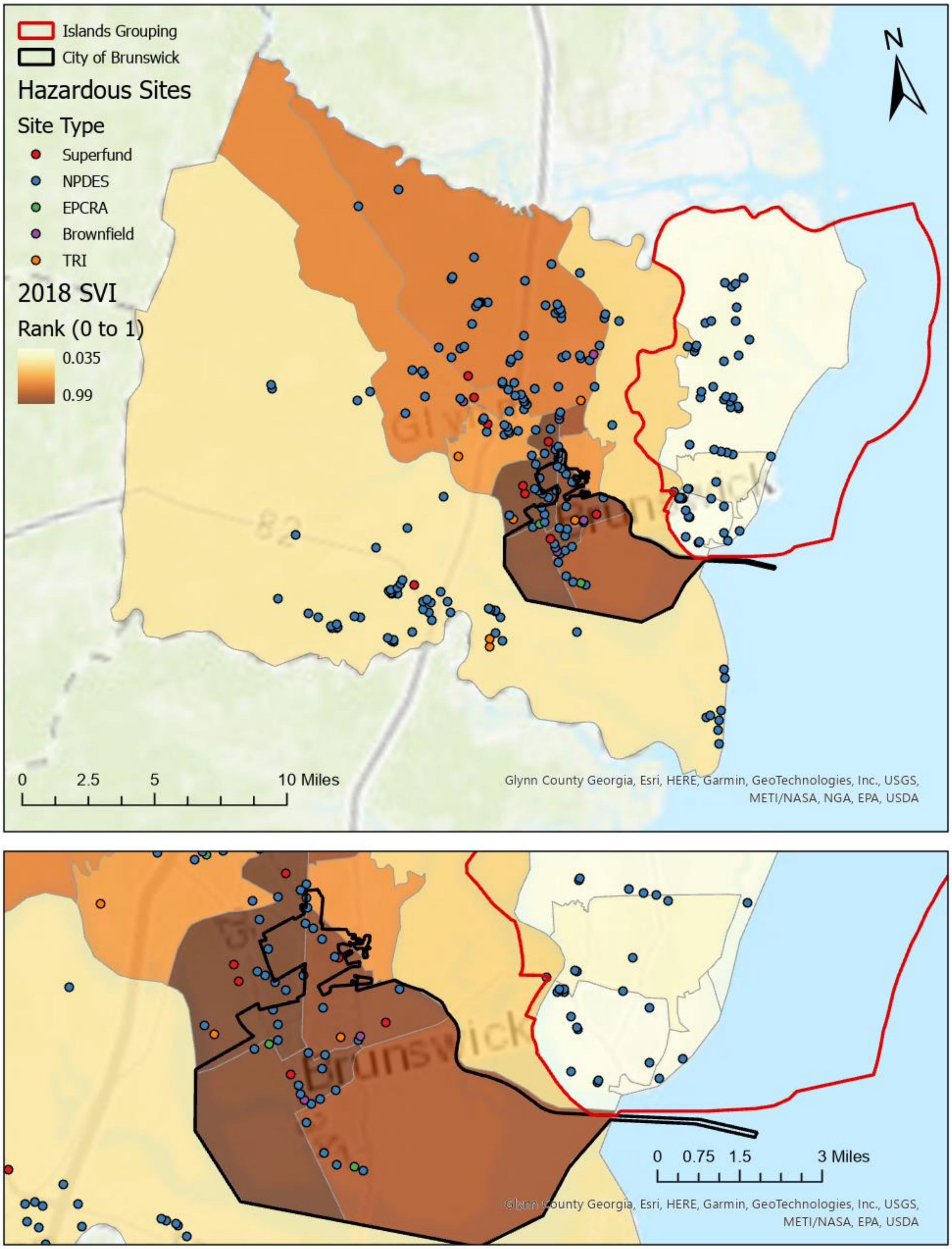


Figure 5: Distribution of Active TRI sites per year, and the Contaminated Media at these Sites



Map 1: Spatial Distribution of Hazardous Sites Active in 2021 in Glynn County

Table 2: Climate Events Affecting Glynn County during the Study Period, and the Number of Home Sales Occurring After Each

Climate Event	(1) Count of Sales
Flood March 17, 2003	29,883
Flood March 31, 2003	29,810
Flood Sept. 14, 2004	26,423
Tropical Storm May 31, 2007	19,667
Flood Aug. 28, 2008	18,011
Tropical Storm June 5, 2013	13,641
Flood May 1, 2014	12,573
Tropical Storm June 5, 2016	9,355
Tropical Storm Sept. 13, 2016	8,810
Hurricane Matthew 2016	8,734
Flood Oct. 16, 2016	8,660
Flood Sept. 19, 2017	6,941
Hurricane Michael 2018	4,925
Wildfire March 20, 2021	165
Observations	35,553

Table 3: The Effect of Trimming Duplicates, Missing Data, and Outliers from the Set of Property Sales

	(1) Full sample	(2) Cleaned sample
Real Sale Price	\$3.3e+05	\$3.0e+05
	(654703.8)	(323366.1)
Construction Year	1988.00	1988.81
	(37.07)	(23.77)
Heated Sq. Ft.	1794.46	1789.55
	(848.0)	(803.9)
Stories	1.23	1.22
	(0.410)	(0.405)
Rooms	6.15	6.14
	(1.871)	(1.569)
Bedrooms	3.18	3.18
	(0.833)	(0.801)
Full Baths	2.27	2.26
	(0.925)	(0.870)
Half Baths	0.32	0.32
	(0.505)	(0.498)
Fireplaces	0.25	0.24
	(0.534)	(0.512)
Number of Sites within One Mile	2.74	2.88
	(4.051)	(4.125)
Number of Sites within Two Miles	8.87	9.29
	(11.37)	(11.54)
Average TCI of Sites within One Mile	0.35	0.36
	(0.485)	(0.483)
Average TCI of Sites within Two Miles	0.51	0.51
	(0.496)	(0.489)
SVI at Property	0.36	0.36
	(0.313)	(0.311)

Average CRI of Sites within One Mile	0.14 (0.289)	0.14 (0.281)
Average CRI of Sites within Two Miles	0.18 (0.252)	0.18 (0.248)
Observations	39679	35553

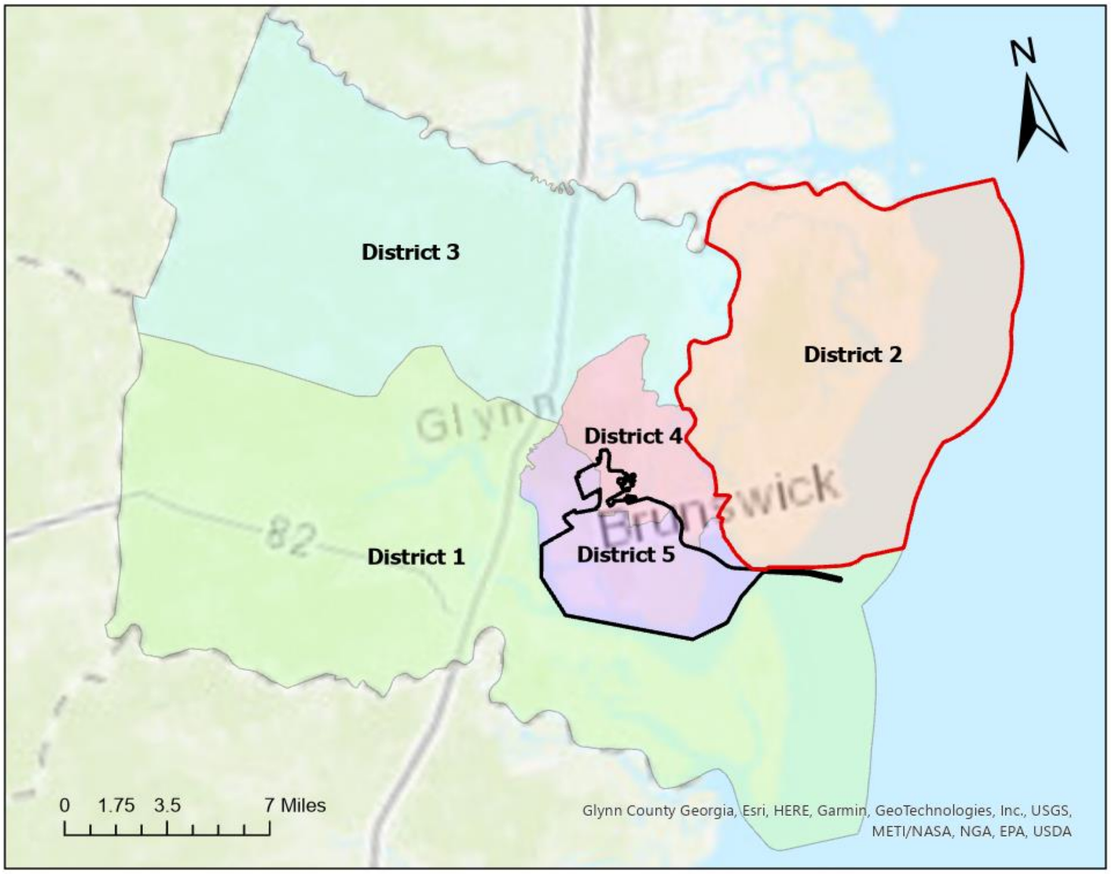
Mean values. Standard Deviations in parentheses.

Table 4: Summary Statistics on Properties Included in the Pooled Regression vs. Repeat-Sales Models

	(1) Pooled, Mainland	(2) Repeat Sales, Mainland	(3) Difference	(4) Pooled, Islands	(5) Repeat Sales, Islands	(6) Difference
Real Sale Price	$1.5e+05	$1.7e+05	-14359.3***	$5.6e+05	$4.5e+05	106706.7***
	(111517.8)	(112720.9)	(-9.27)	(458898.5)	(373796.2)	(15.40)
Construction Year	1985.29	1990.78	-5.493***	1990.81	1989.79	1.011**
	(27.64)	(25.11)	(-15.00)	(21.27)	(16.80)	(3.20)
Heated Sq. Ft.	1713.56	1807.37	-93.80***	2077.49	1668.09	409.4***
	(622.2)	(631.3)	(-10.83)	(1040.1)	(941.2)	(24.70)
Stories	1.09	1.10	-0.00991**	1.39	1.42	-0.0252**
	(0.263)	(0.272)	(-2.68)	(0.475)	(0.499)	(-3.06)
Rooms	6.03	6.16	-0.124***	6.68	5.89	0.793***
	(1.317)	(1.324)	(-6.81)	(1.933)	(1.747)	(25.75)
Bedrooms	3.15	3.24	-0.0832***	3.38	3.01	0.374***
	(0.688)	(0.696)	(-8.69)	(0.891)	(0.933)	(24.21)
Full Baths	1.99	2.13	-0.142***	2.73	2.44	0.285***
	(0.658)	(0.647)	(-15.72)	(1.086)	(0.985)	(16.43)
Half Baths	0.19	0.20	-0.0156**	0.52	0.47	0.0461***
	(0.402)	(0.415)	(-2.76)	(0.567)	(0.557)	(4.87)
Fireplaces	0.21	0.20	0.0123	0.37	0.23	0.138***
	(0.462)	(0.467)	(1.92)	(0.643)	(0.504)	(14.43)
Number of Sites within One Mile	3.48	2.98	0.506***	2.42	2.28	0.142*

	(4.712)	(4.346)	(8.05)	(3.370)	(3.318)	(2.52)
Number of Sites within Two Miles	12.10	10.39	1.711***	6.45	6.32	0.136
	(13.58)	(12.35)	(9.50)	(7.876)	(8.187)	(1.00)
Average TCI of Sites within One Mile	0.31	0.27	0.0395***	0.49	0.43	0.0576***
	(0.428)	(0.413)	(6.78)	(0.563)	(0.533)	(6.27)
Average TCI of Sites within Two Miles	0.45	0.41	0.0374***	0.66	0.61	0.0420***
	(0.407)	(0.410)	(6.62)	(0.560)	(0.568)	(4.40)
SVI at Property	0.57	0.53	0.0423***	0.10	0.09	0.00316*
	(0.276)	(0.267)	(11.24)	(0.0773)	(0.0706)	(2.55)
Average CRI of Sites within One Mile	0.22	0.19	0.0375***	0.05	0.04	0.0106***
	(0.357)	(0.330)	(7.88)	(0.0903)	(0.0731)	(7.79)
Average CRI of Sites within Two Miles	0.28	0.24	0.0354***	0.07	0.06	0.00936***
	(0.295)	(0.282)	(8.88)	(0.0832)	(0.0720)	(7.23)
Observations	11255	9772	21027	5973	8553	14526

Mean values. Standard Deviations in parentheses (1), (2), (4), and (5). t statistics in parentheses (3) and (6).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



Map 2: Glynn County Commission Districts

Table 5: Spatial Differences in Contamination, Climate, and Compound Risks as well as Social Vulnerability

	(1) District One	(2) District Two	(3) District 3	(4) District 4	(5) District 5	(6) ANOVA
Normalized Sale Price	$96.10	$294.72	$99.11	$87.62	$61.61	3.6e+04***
	(59.92)	(260.0)	(51.44)	(45.38)	(55.10)	(0.000)
TCI at Properties	1.14	1.44	0.77	0.95	0.95	973.32***
	(0.629)	(0.588)	(0.466)	(0.542)	(0.442)	(0.000)
SVI at Property	0.31	0.09	0.52	0.78	0.89	1.0e+04***
	(0.144)	(0.0734)	(0.185)	(0.183)	(0.112)	(0.000)
Number of Sites within One Mile	1.59	2.34	2.02	4.64	7.98	5.1e+03***
	(2.672)	(3.340)	(3.077)	(4.939)	(6.172)	(0.000)
Number of Sites within Two Miles	6.06	6.37	8.13	16.34	23.87	5.2e+03***
	(7.769)	(8.061)	(10.05)	(15.02)	(15.14)	(0.000)
Average TCI of Sites within One Mile	0.22	0.46	0.10	0.30	0.89	7.5e+03***
	(0.382)	(0.546)	(0.203)	(0.333)	(0.443)	(0.000)
Average TCI of Sites within Two Miles	0.40	0.63	0.23	0.44	0.91	7.3e+03***
	(0.464)	(0.566)	(0.291)	(0.267)	(0.227)	(0.000)
Average CRI of Sites within One Mile	0.08	0.05	0.05	0.23	0.82	2.4e+04***
	(0.163)	(0.0808)	(0.110)	(0.258)	(0.426)	(0.000)
Average CRI of Sites within Two Miles	0.13	0.06	0.13	0.35	0.73	1.3e+04***
	(0.174)	(0.0769)	(0.180)	(0.242)	(0.228)	(0.000)
Observations	7189	14526	6665	4161	3012	

Mean values reported. Standard Deviations in parentheses Columns 1-5. Pr > Chi2 in parentheses Column (6).
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Comparison between One- and Two-Mile Search Distances for Mainland Property Sales

	(1) One Mile	(2) Two Miles	(3) One Mile	(4) Two Miles
Count of Hazardous Sites	-0.0239***	-0.00903**	-0.0230***	-0.00965**
	(0.00607)	(0.00278)	(0.00612)	(0.00297)
Average TCI of Sites	0.0632*	0.122**		
	(0.0264)	(0.0370)		
Site Count * Sites TCI	-0.0115*	-0.0129***		
	(0.00496)	(0.00324)		
Average CRI at Sites			0.0623	0.0953
			(0.0342)	(0.0678)
Site Count * Sites CRI			-0.0157**	-0.0155***
			(0.00578)	(0.00364)
N	19382	17870	19382	17870
R-squared	0.442	0.459	0.442	0.459
Adj. R-squared	0.434	0.450	0.434	0.450

Clustered standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Comparison between One- and Two-Mile Search Distances for Island Property Sales

	(1) One Mile	(2) Two Miles	(3) One Mile	(4) Two Miles
Count of Hazardous Sites	0.00382	0.00815	0.00375	0.00883*
	(0.00748)	(0.00645)	(0.00467)	(0.00354)
Average TCI of Sites	-0.0304	-0.0593*		
	(0.0257)	(0.0237)		
Site Count * Sites TCI	-0.00592	-0.00686		
	(0.00581)	(0.00427)		
Average CRI at Sites			-0.151	0.0886
			(0.162)	(0.158)
Site Count * Sites CRI			-0.0492	-0.0676***
			(0.0240)	(0.0150)
N	14499	13998	14499	13998
R-squared	0.616	0.630	0.616	0.629
Adj. R-squared	0.611	0.625	0.611	0.624

Clustered standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Pooled Regression Model with Site Types Aggregated

	(1) Mainland with TCI	(2) Islands with TCI	(3) Mainland with CRI	(4) Islands with CRI
Count of Hazardous Sites	-0.0241***	0.00382	-0.0232***	0.00375
	(0.00607)	(0.00748)	(0.00614)	(0.00467)
Property within 1 mile of NPL	0.0303	0	0.0261	0
	(0.0361)	(.)	(0.0373)	(.)
Average TCI of Sites	0.0609*	-0.0304		
	(0.0265)	(0.0257)		
Site Count * Sites TCI	-0.0115*	-0.00592		
	(0.00498)	(0.00581)		
Average CRI at Sites			0.0592	-0.151
			(0.0346)	(0.162)
Site Count * Sites CRI			-0.0157**	-0.0492
			(0.00580)	(0.0240)
TCI at Property	-0.0162	0.0123		
	(0.0355)	(0.0230)		
CRI at Property			-0.0521*	0.155
			(0.0229)	(0.115)
SVI at Property	-0.102	0.369		
	(0.0948)	(0.233)		
Flood March 17, 2003	0.187*	-0.172*	0.185*	-0.172*
	(0.0742)	(0.0707)	(0.0740)	(0.0776)
Flood March 17, 2003 * Property Flood Risk	0.320	0.955***	0.359	0.953***
	(0.564)	(0.245)	(0.522)	(0.221)
Flood March 31, 2003	-0.0364	0.0510	-0.0354	0.0488
	(0.118)	(0.0665)	(0.118)	(0.0674)
Flood March 31, 2003 * Property Flood Risk	-0.226	-0.421	-0.247	-0.414
	(0.579)	(0.240)	(0.573)	(0.255)

Flood Sept. 14, 2004	0.0685	0.176***	0.0679	0.173***
	(0.0808)	(0.0325)	(0.0806)	(0.0299)
Flood Sept 14, 2004 * Property Flood Risk	0.281	-0.298	0.285	-0.282
	(0.204)	(0.162)	(0.204)	(0.154)
Tropical Storm May 31, 2007	0.117*	0.0665	0.116*	0.0633
	(0.0506)	(0.122)	(0.0501)	(0.125)
TS May 31, 2007 *Property Storm Surge Cat 1 Risk	-0.575	-0.416	-0.546	-0.404
	(0.307)	(0.437)	(0.303)	(0.438)
Flood Aug. 28, 2008	-0.0580	0.0530	-0.0577	0.0625
	(0.0394)	(0.0800)	(0.0378)	(0.0834)
Flood Aug. 28, 2008 * Property Flood Risk	-0.0487	-0.168	-0.0340	-0.188
	(0.181)	(0.201)	(0.180)	(0.212)
Tropical Storm June 5, 2013	0.0499	0.0236	0.0465	0.0261
	(0.0348)	(0.0796)	(0.0342)	(0.0806)
TS June 5, 2013 * Property Storm Surge Cat 1 Risk	-0.594	-0.346	-0.547	-0.348
	(0.421)	(0.535)	(0.419)	(0.540)
Flood May 1, 2014	-0.0320	0.0867	-0.0332	0.102
	(0.0616)	(0.0583)	(0.0617)	(0.0557)
Flood May 1, 2014 * Property Flood Risk	0.105	0.0884	0.114	0.0338
	(0.153)	(0.210)	(0.152)	(0.203)
Tropical Storm June 5, 2016	0.00988	-0.0530	0.0105	-0.0403
	(0.0718)	(0.160)	(0.0720)	(0.155)
TS June 5, 2016 * Property Storm Surge	0.962	0.833	0.960	0.746

Cat 1 Risk				
	(0.695)	(1.190)	(0.706)	(1.159)
Tropical Storm Sept. 13, 2016	-0.233	-0.0775	-0.236	-0.0935
	(0.270)	(0.176)	(0.271)	(0.170)
TS Sept. 13, 2016 * Property Storm Surge Cat 1 Risk	-0.385	0.430	-0.355	0.576
	(0.789)	(1.358)	(0.802)	(1.310)
Hurricane Matthew 2016	0.0418	0.0270	0.0435	0.0270
	(0.200)	(0.0409)	(0.200)	(0.0374)
Flood Oct. 16, 2016	0.275	0.0738	0.275	0.0636
	(0.154)	(0.0863)	(0.155)	(0.0839)
Flood Oct. 16, 2016 * Property Flood Risk	-0.358*	-0.310	-0.368*	-0.285
	(0.174)	(0.185)	(0.172)	(0.185)
Flood Sept. 19, 2017	-0.0161	-0.0229	-0.0172	-0.0274
	(0.0836)	(0.0520)	(0.0833)	(0.0556)
Flood Sept. 19, 2017 * Property Flood Risk	-0.000633	0.103	0.0177	0.140
	(0.222)	(0.203)	(0.222)	(0.210)
Hurricane Michael 2018	-0.0135	0.0233	-0.0116	0.0215
	(0.0370)	(0.0190)	(0.0373)	(0.0191)
Wildfire March 20, 2021	0.0318	0.0219	0.0329	0.0230
	(0.0343)	(0.0435)	(0.0339)	(0.0433)
N	19382	14499	19382	14499
R-squared	0.442	0.616	0.442	0.616
Adj. R-squared	0.434	0.611	0.434	0.611

Clustered standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Pooled Regression Model with Site Types Disaggregated

	(1) Mainland with TCI	(2) Islands with TCI	(3) Mainland with CRI	(4) Islands with CRI
Count of Superfund Sites	0.00308	0	-0.00220	0
	(0.0333)	(.)	(0.0301)	(.)
Property within 1 mile of NPL	0.0535	0	0.0518	0
	(0.0522)	(.)	(0.0532)	(.)
Count of NPDES Permits	-0.0196*	-0.00308	-0.0174*	0.00137
	(0.00795)	(0.0102)	(0.00753)	(0.00594)
Count of EPCRA Sites	-0.0486***	-0.00955	-0.0472***	-0.00391
	(0.00879)	(0.0219)	(0.00819)	(0.0208)
Count of Brownfields	-0.184*	0	-0.181*	0
	(0.0748)	(.)	(0.0743)	(.)
Count of TRI Sites	-0.0219	0	-0.0128	0
	(0.0280)	(.)	(0.0242)	(.)
Average TCI at Superfund Sites	-0.198**	0		
	(0.0593)	(.)		
Average CRI at Superfund Sites			-0.251***	0
			(0.0668)	(.)
Average TCI at NPDES Permits	-0.0158	0.00370		
	(0.0303)	(0.0201)		
Average CRI at NPDES Permits			0.00735	-0.117
			(0.0410)	(0.140)
Average TCI at EPCRA Sites	-0.146	-0.108		
	(0.0732)	(0.0618)		
Average CRI at EPCRA Sites			-0.193*	0.216
			(0.0874)	(0.682)

Average TCI at Brownfields	-0.0618	0		
	(0.0386)	(.)		
Average CRI at Brownfields			-0.0522	0
			(0.0392)	(.)
Average TCI at TRI Sites	0.0228	0		
	(0.0524)	(.)		
Average CRI at TRI Sites			-0.164	0
			(0.211)	(.)
Superfund Site Count * TCI	-0.0240	0		
	(0.0284)	(.)		
Superfund Site Count * CRI			-0.0155	0
			(0.0289)	(.)
NPDES Permit Count * TCI	0.000402	-0.00220		
	(0.0128)	(0.00728)		
NPDES Permit Count * CRI			-0.00541	-0.0407
			(0.0123)	(0.0326)
EPCRA Site Count * TCI	0.0278	0.0435		
	(0.0201)	(0.0302)		
EPCRA Site Count * CRI			0.0345	-0.306
			(0.0239)	(0.461)
Brownfields Site Count * TCI	0.127^{*}	0		
	(0.0604)	(.)		
Brownfields Site Count * CRI			0.123^{*}	0
			(0.0606)	(.)
TRI Site Count * TCI	0.0263	0		

	(0.0390)	(.)		
TRI Site Count * CRI			0.0671	0
			(0.0966)	(.)
TCI at Property	-0.0119	0.0143		
	(0.0364)	(0.0236)		
CRI at Property			-0.0260	0.166
			(0.0226)	(0.112)
SVI at Property	-0.104	0.519*		
	(0.0889)	(0.231)		
Flood March 17, 2003	0.181*	-0.168*	0.179*	-0.173*
	(0.0728)	(0.0687)	(0.0715)	(0.0787)
Flood March 17, 2003 * Property Flood Risk	0.318	0.931***	0.330	0.949***
	(0.546)	(0.252)	(0.503)	(0.223)
Flood March 31, 2003	-0.0308	0.0492	-0.0288	0.0494
	(0.116)	(0.0674)	(0.115)	(0.0662)
Flood March 31, 2003 * Property Flood Risk	-0.225	-0.406	-0.232	-0.410
	(0.558)	(0.252)	(0.554)	(0.256)
Flood Sept. 14, 2004	0.0700	0.173***	0.0703	0.175***
	(0.0809)	(0.0306)	(0.0812)	(0.0322)
Flood Sept 14, 2004 * Property Flood Risk	0.262	-0.284	0.249	-0.288
	(0.215)	(0.152)	(0.219)	(0.163)
Tropical Storm May 31, 2007	0.114*	0.0719	0.113*	0.0623
	(0.0488)	(0.122)	(0.0485)	(0.123)
TS May 31, 2007 *Property Storm Surge Cat 1 Risk	-0.389	-0.452	-0.396	-0.395
	(0.315)	(0.413)	(0.309)	(0.437)
Flood Aug. 28, 2008	-0.0634	0.0596	-0.0626	0.0634
	(0.0389)	(0.0833)	(0.0383)	(0.0815)

Flood Aug. 28, 2008 * Property Flood Risk	-0.0546	-0.191	-0.0361	-0.191
	(0.178)	(0.206)	(0.183)	(0.214)
Tropical Storm June 5, 2013	0.0519	0.0182	0.0462	0.0278
	(0.0328)	(0.0773)	(0.0321)	(0.0804)
TS June 5, 2013 * Property Storm Surge Cat 1 Risk	-0.653	-0.312	-0.574	-0.364
	(0.417)	(0.525)	(0.411)	(0.540)
Flood May 1, 2014	-0.0369	0.0911	-0.0378	0.102
	(0.0606)	(0.0580)	(0.0618)	(0.0569)
Flood May 1, 2014 * Property Flood Risk	0.166	0.0810	0.167	0.0333
	(0.152)	(0.211)	(0.152)	(0.207)
Tropical Storm June 5, 2016	0.00583	-0.0549	0.00390	-0.0421
	(0.0735)	(0.155)	(0.0738)	(0.153)
TS June 5, 2016 * Property Storm Surge Cat 1 Risk	1.013	0.838	0.999	0.759
	(0.699)	(1.149)	(0.703)	(1.141)
Tropical Storm Sept. 13, 2016	-0.224	-0.0740	-0.230	-0.0940
	(0.271)	(0.168)	(0.273)	(0.166)
TS Sept. 13, 2016 * Property Storm Surge Cat 1 Risk	-0.549	0.407	-0.485	0.571
	(0.810)	(1.321)	(0.814)	(1.293)
Hurricane Matthew 2016	0.0437	0.0323	0.0455	0.0293
	(0.202)	(0.0399)	(0.203)	(0.0369)
Flood Oct. 16, 2016	0.280	0.0713	0.283	0.0632
	(0.155)	(0.0854)	(0.156)	(0.0824)
Flood Oct. 16, 2016 *	-0.362^{*}	-0.315	-0.362^{*}	-0.288

Property Flood Risk				
	(0.170)	(0.179)	(0.167)	(0.184)
Flood Sept. 19, 2017	-0.0232	-0.0199	-0.0236	-0.0255
	(0.0820)	(0.0522)	(0.0813)	(0.0554)
Flood Sept. 19, 2017 * Property Flood Risk	0.0656	0.0915	0.0676	0.134
	(0.225)	(0.196)	(0.217)	(0.207)
Hurricane Michael 2018	-0.0151	0.0237	-0.0134	0.0224
	(0.0363)	(0.0193)	(0.0369)	(0.0193)
Wildfire March 20, 2021	0.0365	0.0277	0.0416	0.0235
	(0.0363)	(0.0410)	(0.0364)	(0.0421)
N	19382	14499	19382	14499
R-squared	0.444	0.616	0.445	0.616
Adj. R-squared	0.435	0.611	0.436	0.611

Clustered standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Repeat-Sales Model with Site Types Aggregated

	(1) Mainland with TCI	(2) Islands with TCI	(3) Mainland with CRI	(4) Islands with CRI
Count of Hazardous Sites	-0.0325***	-0.0107	-0.0321***	-0.00354
	(0.00679)	(0.0139)	(0.00683)	(0.00753)
Property within 1 mile of NPL	0	0	0	0
	(.)	(.)	(.)	(.)
Average TCI of Sites	0.0574	-0.0388		
	(0.0598)	(0.0210)		
Site Count * Sites TCI	0.00286	0.00429		
	(0.00617)	(0.00976)		
Average CRI at Sites			0.0514	-0.157
			(0.0739)	(0.137)
Site Count * Sites CRI			0.00175	-0.0135
			(0.00709)	(0.0373)
TCI at Property	0	0		
	(.)	(.)		
SVI at Property	-0.0596	0.391		
	(0.137)	(0.264)		
CRI at Property			0.00448	0.168
			(0.0909)	(0.163)
Flood March 17, 2003	0.103	-0.147	0.101	-0.146
	(0.222)	(0.112)	(0.222)	(0.113)
Flood March 17, 2003 * Property Flood Risk	0.363	0.804	0.373	0.798
	(1.191)	(0.441)	(1.200)	(0.444)
Flood March 31, 2003	0.110	0.0962	0.111	0.0946
	(0.207)	(0.115)	(0.207)	(0.117)
Flood March 31, 2003 * Property Flood Risk	-0.352	-0.639	-0.354	-0.630
	(1.061)	(0.397)	(1.064)	(0.404)

Flood Sept. 14, 2004	0.113	0.186**	0.113	0.183*
	(0.0831)	(0.0698)	(0.0832)	(0.0703)
Flood Sept 14, 2004 * Property Flood Risk	0.520*	-0.242	0.521*	-0.227
	(0.244)	(0.178)	(0.243)	(0.177)
Tropical Storm May 31, 2007	0.217**	-0.0217	0.217**	-0.0312
	(0.0773)	(0.0799)	(0.0776)	(0.0803)
TS May 31, 2007 *Property Storm Surge Cat 1 Risk	-0.449	0.542	-0.421	0.598
	(0.626)	(0.512)	(0.631)	(0.515)
Flood Aug. 28, 2008	-0.134	0.0840	-0.134	0.0901
	(0.0886)	(0.0886)	(0.0884)	(0.0885)
Flood Aug. 28, 2008 * Property Flood Risk	-0.158	-0.142	-0.157	-0.150
	(0.232)	(0.139)	(0.234)	(0.141)
Tropical Storm June 5, 2013	0.0778	0.0749	0.0760	0.0770
	(0.0633)	(0.0747)	(0.0628)	(0.0720)
TS June 5, 2013 * Property Storm Surge Cat 1 Risk	-0.793*	-0.448	-0.776	-0.456
	(0.401)	(0.470)	(0.410)	(0.453)
Flood May 1, 2014	0.0262	0.129	0.0222	0.143*
	(0.0742)	(0.0669)	(0.0734)	(0.0682)
Flood May 1, 2014 * Property Flood Risk	-0.0793	-0.0385	-0.0670	-0.0771
	(0.185)	(0.110)	(0.182)	(0.116)
Tropical Storm June 5, 2016	-0.146	-0.0834	-0.146	-0.0743
	(0.188)	(0.0652)	(0.188)	(0.0629)
TS June 5, 2016 * Property Storm Surge Cat 1 Risk	2.282	1.377**	2.282	1.308**

	(1.378)	(0.506)	(1.377)	(0.475)
Tropical Storm Sept. 13, 2016	-0.418	0.0533	-0.419	0.0472
	(0.401)	(0.0981)	(0.399)	(0.0964)
TS Sept. 13, 2016 * Property Storm Surge Cat 1 Risk	-1.431	-0.635	-1.400	-0.532
	(1.466)	(0.534)	(1.467)	(0.499)
Hurricane Matthew 2016	0.121	0.0268	0.120	0.0200
	(0.406)	(0.0991)	(0.405)	(0.0996)
Flood Oct. 16, 2016	0.566*	0.00850	0.568*	0.00411
	(0.266)	(0.0792)	(0.266)	(0.0777)
Flood Oct. 16, 2016 * Property Flood Risk	-0.130	-0.173	-0.148	-0.163
	(0.336)	(0.119)	(0.328)	(0.117)
Flood Sept. 19, 2017	0.101	0.00570	0.0998	-0.00363
	(0.120)	(0.0523)	(0.120)	(0.0508)
Flood Sept. 19, 2017 * Property Flood Risk	-0.403	-0.0985	-0.385	-0.0490
	(0.294)	(0.113)	(0.293)	(0.104)
Hurricane Michael 2018	-0.0177	0.0263	-0.0155	0.0247
	(0.0616)	(0.0309)	(0.0616)	(0.0313)
Wildfire March 20, 2021	-0.0330	-0.0135	-0.0314	-0.0145
	(0.0752)	(0.0415)	(0.0752)	(0.0415)
N	19382	14499	19382	14499
R-squared	0.0809	0.0949	0.0806	0.0933
Adj. R-squared	0.0781	0.0892	0.0777	0.0875

Clustered standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Repeat-Sales Model with Site Types Disaggregated

	(1) Mainland with TCI	(2) Islands with TCI	(3) Mainland with CRI	(4) Islands with CRI
Count of Superfund Sites	-0.0503	0	0.00518	0
	(0.0605)	(.)	(0.0594)	(.)
Property within 1 mile of NPL	0	0	0	0
	(.)	(.)	(.)	(.)
Count of NPDES Permits	-0.0264**	-0.00739	-0.0258**	-0.00492
	(0.00954)	(0.0143)	(0.00945)	(0.00786)
Count of EPCRA Sites	-0.0418**	-0.0197	-0.0412**	-0.00133
	(0.0139)	(0.0435)	(0.0136)	(0.0330)
Count of Brownfields	-0.102	0	-0.0944	0
	(0.117)	(.)	(0.117)	(.)
Count of TRI Sites	-0.0641	0	-0.0467	0
	(0.0401)	(.)	(0.0417)	(.)
Average TCI at Superfund Sites	0.0755	0		
	(0.135)	(.)		
Average CRI at Superfund Sites			-0.131	0
			(0.156)	(.)
Average TCI at NPDES Permits	-0.0197	-0.0398		
	(0.0366)	(0.0255)		
Average CRI at NPDES Permits			-0.000933	-0.106
			(0.0420)	(0.129)
Average TCI at EPCRA Sites	-0.0414	0.0230		
	(0.0873)	(0.0618)		
Average CRI at EPCRA Sites			-0.0488	-1.181
			(0.0939)	(0.749)

Average TCI at Brownfields	-0.0316 (0.0527)	0 (.)		
Average CRI at Brownfields			-0.0134 (0.0517)	0 (.)
Average TCI at TRI Sites	0.0809 (0.106)	0 (.)		
Average CRI at TRI Sites			0.165 (0.339)	0 (.)
Superfund Site Count * TCI	-0.223* (0.112)	0 (.)		
Superfund Site Count * CRI			-0.272* (0.111)	0 (.)
NPDES Permit Count * TCI	0.0193 (0.0141)	0.00244 (0.00974)		
NPDES Permit Count * CRI			0.0240 (0.0149)	0.00591 (0.0394)
EPCRA Site Count * TCI	-0.00184 (0.0269)	0.00419 (0.0324)		
EPCRA Site Count * CRI			-0.0146 (0.0318)	0.601 (0.326)
Brownfields Site Count * TCI	0.0495 (0.0978)	0 (.)		
Brownfields Site Count * CRI			0.0426 (0.0994)	0 (.)
TRI Site Count * TCI	0.00184 (0.0770)	0 (.)		
TRI Site Count * CRI			-0.0867 (0.164)	0 (.)
TCI at Property	0 (.)	0 (.)		

SVI at Property	-0.0594	0.387		
	(0.143)	(0.261)		
CRI at Property			0.0371	0.209
			(0.0850)	(0.174)
Flood March 17, 2003	0.113	-0.148	0.109	-0.145
	(0.223)	(0.113)	(0.223)	(0.113)
Flood March 17, 2003 * Property Flood Risk	0.347	0.796	0.359	0.800
	(1.180)	(0.449)	(1.182)	(0.448)
Flood March 31, 2003	0.102	0.0962	0.105	0.0945
	(0.207)	(0.116)	(0.207)	(0.117)
Flood March 31, 2003 * Property Flood Risk	-0.311	-0.631	-0.316	-0.633
	(1.060)	(0.405)	(1.062)	(0.406)
Flood Sept. 14, 2004	0.114	0.187*	0.114	0.181*
	(0.0834)	(0.0708)	(0.0835)	(0.0710)
Flood Sept 14, 2004 * Property Flood Risk	0.504*	-0.246	0.501*	-0.221
	(0.245)	(0.180)	(0.245)	(0.179)
Tropical Storm May 31, 2007	0.212**	-0.0222	0.209**	-0.0290
	(0.0776)	(0.0817)	(0.0779)	(0.0810)
TS May 31, 2007 *Property Storm Surge Cat 1 Risk	-0.266	0.546	-0.248	0.576
	(0.643)	(0.510)	(0.641)	(0.517)
Flood Aug. 28, 2008	-0.134	0.0849	-0.134	0.0871
	(0.0892)	(0.0837)	(0.0890)	(0.0874)
Flood Aug. 28, 2008 * Property Flood Risk	-0.173	-0.132	-0.178	-0.147
	(0.241)	(0.137)	(0.246)	(0.141)
Tropical Storm June 5, 2013	0.0808	0.0740	0.0788	0.0724
	(0.0625)	(0.0743)	(0.0621)	(0.0712)
TS June 5, 2013 * Property	-0.812	-0.445	-0.772	-0.433

Storm Surge Cat 1 Risk				
	(0.414)	(0.486)	(0.419)	(0.463)
Flood May 1, 2014	0.0257	0.129*	0.0208	0.146*
	(0.0748)	(0.0643)	(0.0741)	(0.0675)
Flood May 1, 2014 * Property Flood Risk	-0.0558	-0.0387	-0.0467	-0.0895
	(0.187)	(0.103)	(0.184)	(0.113)
Tropical Storm June 5, 2016	-0.144	-0.0831	-0.147	-0.0776
	(0.187)	(0.0652)	(0.187)	(0.0681)
TS June 5, 2016 * Property Storm Surge Cat 1 Risk	2.251	1.380**	2.247	1.323*
	(1.369)	(0.505)	(1.369)	(0.498)
Tropical Storm Sept. 13, 2016	-0.403	0.0521	-0.402	0.0487
	(0.402)	(0.0974)	(0.401)	(0.0980)
TS Sept. 13, 2016 * Property Storm Surge Cat 1 Risk	-1.628	-0.629	-1.595	-0.554
	(1.446)	(0.534)	(1.453)	(0.509)
Hurricane Matthew 2016	0.135	0.0262	0.141	0.0276
	(0.406)	(0.0982)	(0.406)	(0.0985)
Flood Oct. 16, 2016	0.555*	0.00597	0.548*	0.00110
	(0.267)	(0.0792)	(0.268)	(0.0783)
Flood Oct. 16, 2016 * Property Flood Risk	-0.122	-0.174	-0.113	-0.159
	(0.339)	(0.119)	(0.333)	(0.118)
Flood Sept. 19, 2017	0.0937	0.00656	0.0962	-0.00377
	(0.122)	(0.0521)	(0.121)	(0.0507)
Flood Sept. 19, 2017 * Property Flood Risk	-0.319	-0.0984	-0.324	-0.0489
	(0.312)	(0.114)	(0.303)	(0.107)
Hurricane Michael 2018	-0.0301	0.0258	-0.0268	0.0246
	(0.0613)	(0.0307)	(0.0611)	(0.0311)
Wildfire March 20, 2021	-0.0369	-0.0139	-0.0333	-0.00784

	(0.0761)	(0.0420)	(0.0755)	(0.0417)
N	19382	14499	19382	14499
R-squared	0.0824	0.0950	0.0835	0.0939
Adj. R-squared	0.0790	0.0891	0.0801	0.0880

Clustered standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Table 1: Initial Investigation of Different Property Markets

	(1) Glynn County	(2) Islands Only
Count of Hazardous Sites	-0.0255***	0.00382
	(0.00543)	(0.00748)
Property within 1 mile of NPL	0.0626	0
	(0.0437)	(.)
Average TCI of Sites	-0.0117	-0.0304
	(0.0220)	(0.0257)
Site Count * Sites TCI	0.000175	-0.00592
	(0.00437)	(0.00581)
TCI at Property	0.0126	0.0123
	(0.0238)	(0.0230)
SVI at Property	0.00118	0.369
	(0.0979)	(0.233)
Flood March 17, 2003	0.0649	-0.172*
	(0.0701)	(0.0707)
Flood March 17, 2003 * Property Flood Risk	0.446	0.955***
	(0.366)	(0.245)
Flood March 31, 2003	-0.0147	0.0510
	(0.0896)	(0.0665)
Flood March 31, 2003 * Property Flood Risk	-0.164	-0.421
	(0.375)	(0.240)
Flood Sept. 14, 2004	0.0971	0.176***
	(0.0516)	(0.0325)
Flood Sept 14, 2004 * Property Flood Risk	0.0593	-0.298
	(0.127)	(0.162)
Tropical Storm May 31, 2007	0.126*	0.0665
	(0.0515)	(0.122)
TS May 31, 2007 *Property Storm Surge Cat 1 Risk	-0.729*	-0.416
	(0.293)	(0.437)

Flood Aug. 28, 2008	-0.0131	0.0530
	(0.0497)	(0.0800)
Flood Aug. 28, 2008 * Property Flood Risk	-0.292	-0.168
	(0.179)	(0.201)
Tropical Storm June 5, 2013	0.0284	0.0236
	(0.0424)	(0.0796)
TS June 5, 2013 * Property Storm Surge Cat 1 Risk	-0.356	-0.346
	(0.372)	(0.535)
Flood May 1, 2014	0.0195	0.0867
	(0.0478)	(0.0583)
Flood May 1, 2014 * Property Flood Risk	0.148	0.0884
	(0.153)	(0.210)
Tropical Storm June 5, 2016	-0.0214	-0.0530
	(0.0786)	(0.160)
TS June 5, 2016 * Property Storm Surge Cat 1 Risk	0.925	0.833
	(0.664)	(1.190)
Tropical Storm Sept. 13, 2016	-0.130	-0.0775
	(0.194)	(0.176)
TS Sept. 13, 2016 * Property Storm Surge Cat 1 Risk	-0.216	0.430
	(0.788)	(1.358)
Hurricane Matthew 2016	0.0632	0.0270
	(0.116)	(0.0409)
Flood Oct. 16, 2016	0.155	0.0738
	(0.0906)	(0.0863)
Flood Oct. 16, 2016 * Property Flood Risk	-0.336*	-0.310
	(0.153)	(0.185)
Flood Sept. 19, 2017	-0.00232	-0.0229
	(0.0669)	(0.0520)
Flood Sept. 19, 2017 * Property Flood Risk	-0.0211	0.103

	(0.173)	(0.203)
Hurricane Michael 2018	0.00935	0.0233
	(0.0261)	(0.0190)
Wildfire March 20, 2021	0.0345	0.0219
	(0.0219)	(0.0435)
N	33881	14499
R-squared	0.680	0.616
Adj. R-squared	0.676	0.611

Clustered standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Table 2: Pooled Regression Model with Site Types Aggregated, Numerical Property Covariates Reported

	(1) Mainland with TCI	(2) Islands with TCI	(3) Mainland with CRI	(4) Islands with CRI
Count of Hazardous Sites	-0.0241^{***}	0.00382	-0.0232^{***}	0.00375
	(0.00607)	(0.00748)	(0.00614)	(0.00467)
Property within 1 mile of NPL	0.0303	0	0.0261	0
	(0.0361)	(.)	(0.0373)	(.)
Average TCI of Sites	0.0609^{*}	-0.0304		
	(0.0265)	(0.0257)		
Average CRI at Sites			0.0592	-0.151
			(0.0346)	(0.162)
Site Count * Sites TCI	-0.0115^{*}	-0.00592		
	(0.00498)	(0.00581)		
Site Count * Sites CRI			-0.0157^{**}	-0.0492
			(0.00580)	(0.0240)
TCI at Property	-0.0162	0.0123		
	(0.0355)	(0.0230)		
CRI at Property			-0.0521^{*}	0.155
			(0.0229)	(0.115)
SVI at Property	-0.102	0.369		
	(0.0948)	(0.233)		
Construction Year	-0.000420	-0.00338^{***}	-0.000385	-0.00334^{***}
	(0.00105)	(0.000769)	(0.00104)	(0.000771)
Heated Sq. Ft.	0.000170^{***}	0.000143^{***}	0.000171^{***}	0.000142^{***}
	(0.0000212)	(0.0000147)	(0.0000216)	(0.0000137)
Stories	0.174^{***}	0.132^{***}	0.174^{***}	0.133^{***}
	(0.0358)	(0.0199)	(0.0359)	(0.0192)
Rooms	-0.00446	-0.00842	-0.00465	-0.00911
	(0.00676)	(0.00509)	(0.00679)	(0.00499)

Bedrooms	-0.0144	-0.0108	-0.0143	-0.00980
	(0.0123)	(0.00772)	(0.0124)	(0.00833)
Full Baths	0.0683***	0.0913***	0.0684***	0.0907***
	(0.0164)	(0.0148)	(0.0162)	(0.0149)
Half Baths	-0.0298*	0.0298**	-0.0297*	0.0299**
	(0.0148)	(0.0102)	(0.0147)	(0.0101)
Fireplaces	0.0642***	0.0226	0.0643***	0.0217
	(0.0103)	(0.0111)	(0.0107)	(0.0113)
N	19382	14499	19382	14499
R-squared	0.442	0.616	0.442	0.616
Adj. R-squared	0.434	0.611	0.434	0.611

Clustered standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Table 3: Global Mean Sea Level Rise and Glynn County Corresponding Depth and Probability

	(1) Glynn County Depth SLR	(2) Glynn County 50-year Cumulative Probability
GMSLR 0.3 m	1.05 ft.	100%
GMSLR 0.5 m	1.31 ft.	96%
GMSLR 1 m	2.30 ft	17%
GMSLR 1.5 m	3.38 ft.	1.3%
GMSLR 2 m	4.59 ft.	0.3%

Data are from Sweet et al. 2017