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Systemic Financial Risk Arising from Residential Flood Losses

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Abstract

Direct damage from flooding at residential properties has typically been categorized as insured, with liabilities accruing to insurers, or uninsured, with costs accruing to property owners. However, residential flooding can also expose lenders and local governments to financial risk, though the distribution of this risk is not well understood. Flood losses are not limited to direct damages, but also include indirect effects such as decreases in property values, which can be substantial, though are rarely well quantified. The combination of direct damage and property value decrease influences rates of mortgage default and property abandonment in the wake of a flood, creating financial risk. In this research, property-level data on sales, mortgages, and insurance claims are used in combination with machine learning techniques and geostatistical

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This analysis was conducted using Python version 3.9.7. Unless otherwise noted in the methods, the data used in this study are publicly available as follows: (i) the USGS National Hydrography High Resolution (NHDPlus) (https://www.usgs.gov/national-hydrography/nhdplus-high-resolution; https://apps.nationalmap.gov/downloader/#/); (ii) the National Oceanic and Atmospheric Administration's composite shoreline (https://shoreline.noaa.gov/data/datasheets/composite.html); (iii) the Height Above Nearest Drainage (HAND) for the Continental US (CONUS) (https://cfim.ornl.gov/data/); (iv) Multi-Resolution Land Characteristics (MLRC) Consortium's National Land Cover Database (NLCD) 2016 (https://www.mrlc.gov/data/nlcd-2016-land-cover-conus); (v) U.S. Department of Agriculture (USDA) Gridded Soil Survey (gSSURGO) (https://gdg.sc.egov.usda.gov/); (vi) buildings (https://www.nconemap.gov/datasets/NCEM-GIS::nc-buildings-footprints-2010/explore?location=35.145413%2C-79.919600%2C7.94) and parcels (https://www.nconemap.gov/datasets/nconemap::north-carolina-parcels-polygons/explore?location=35.143981%2C-79.919650%2C7.91) data were obtained from NC OneMap Geospatial Portal (https://www.nconemap.gov); (vii) federal loan data was obtained from FFEIC (https://ffiec.cfpb.gov/data-publication/snapshot-national-loan-level-dataset) and Fannie Mae (https://capitalmarkets.fanniemae.com/credit-risk-transfer/single-family-credit-risk-transfer/fannie-mae-single-family-loan-performance-data); (viii) federal loan delinquency rates were obtained from the Federal Housing and Finance Administration (https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx). Use of these data sets are described further in Supporting Information S2.

Most of the datasets used to support this analysis and the reproduction code are openly available when possible at the following URL: https://doi.org/10.5281/zenodo.6634028. Select data, including property level flood insurance policies and claims, and property level sales data, contain personally identifiable information and are not publicly available at the scale of individual properties. Property sales data were obtained via the First Street Foundation and purchased from ATTOM (https://www.attomdata.com/data/transactions-mortgage-data/); inquiries for availability may be sent to support@firststreet.org. Flood insurance property and claims data are publicly available in a redacted format via the Federal Emergency Management Association's website (https://www.fema.gov/about/reports-and-data/openfema). The property level version of insurance policies and claims data used in this analysis is confidential, although inquiries regarding availability may be sent to OpenFEMA@fema.dhs.gov.

methods to provide estimates of flood losses that are then utilized to evaluate the risk of default and abandonment in eastern North Carolina following Hurricane Florence (2018). Within the study area, Hurricane Florence generated $366M in observed insured damages and an estimated $1.77B in combined uninsured damages and property value decreases. Property owners, lenders, and local governments were exposed to an additional $562M in potential losses due to increased rates of default and abandonment. Areas with lower pre-flood property values were exposed to greater risk than areas with higher valued properties. Results suggest more highly resolved estimates of a flooding event's systemic financial risk may be useful in developing improved flood resilience strategies.

Plain Language Summary

The financial impacts of flooding are complex and their distribution across different groups is difficult to quantify. Traditionally, the focus has been on estimating damages that directly impact insurers and property owners, but lenders and local governments can also be affected. Following a flood, uninsured damage and reductions in property value can combine to reduce a property owner's equity, hampering their ability to borrow money and recover from the flood. This can lead to mortgage default or even property abandonment, resulting in financial consequences for the property owner, the mortgage lender, and/or the local government.

This research estimates uninsured damage and property value changes throughout eastern North Carolina following Hurricane Florence via a novel machine learning approach, using data on the physical characteristics of residential properties, insurance claims, property sales, and mortgages. Results indicate that uninsured damage and property value decreases combined to be substantial and this combination significantly increased risk of mortgage default and/or abandonment. Lower valued properties experienced higher rates of default and abandonment than high valued properties, with risk varying widely across communities. This type of analysis allows for property-level assistance to be targeted toward the most vulnerable.

1 Introduction

Flood events are society's costliest natural hazards, with impacts expected to rise due to growing hazard exposure and climate change-driven increases in flood frequency and severity (Bates et al., 2020; Hallegatte et al., 2013; Hayhoe et al., 2018; Marsooli et al., 2019). These combined effects have already been observed via recent surges in insured losses at residential properties in the United States: in 2017, the National Flood Insurance Program (NFIP) paid out over $8.7 billion in claims as the nation's primary insurance provider (Kousky, Kunreuther, et al., 2020). As rates of insurance purchase are low, assessments of flood impacts often seek to estimate the amounts of uninsured damage in addition to insured losses(Bradt et al., 2021; Dixon et al., 2006). Simple categories such as insured and uninsured damage, however, are often insufficient to understand the full consequences of flooding events over time and across stakeholders. Losses associated with large flood events are known to create delayed societal effects that are inextricably linked to the success of recovery efforts (Bubeck et al., 2017; Kreibich et al., 2014). This is particularly true when considering flood-related losses at residential properties, which can lead to cascading financial risk that impacts groups well beyond the property owners themselves (Kousky, Kunreuther, et al., 2020). The creation of this type of systemic financial risk following a flood event is an area that remains underexplored.

Research on flood impacts on society has increased as the losses from these events have increased, with growing attention focused on how these events may be rippling through financial systems. Prior studies have correlated the pre-flood financial status of households with the success of their long-term recovery efforts (Billings et al., 2019; Howell & Elliott, 2019; Peacock et al., 2015; Ratcliffe et al., 2020b; Roth Tran & Sheldon, 2019). Other studies have addressed similar questions with respect to linkages between the financial health of lending institutions (Ratnadiwakara & Venugopal, 2020; Schüwer et al., 2019), local governments (Jerch et al., 2020; Painter, 2020; Shi & Varuzzo, 2020) and their resilience in the face of flood-related losses (Barth et al., 2019; Blickle et al., 2022; Brei et al., 2019; Klomp, 2014; Koetter et al., 2020; Noth & Schuewer, 2018). These analyses complement calls to better quantify flood hazard and exposure as a means to improve community flood resilience (Bates et al., 2020; Blessing et al., 2017; Jenkins et al., 2017; Lorie et al., 2020; Woznicki et al., 2019). Flood-related losses can, for example, drive increased likelihood of residential mortgage defaults (Kousky, Palim, et al., 2020) and property abandonment (Maly et al., 2016), and may thereby create financial consequences that are well beyond direct damages (Hellwig, 2009). Despite these trends being observed, few attempts have been made to quantify the cascading financial risks arising from these large flood events.

This study seeks to estimate the distribution of flood-related financial loss and risk across residential property owners, mortgage lenders, and local governments. This is done via a new approach that incorporates consideration of not only losses attributable to direct damages, but also indirect losses in the form of flood-related changes in property value and owner equity. This allows for 1) the quantification of property-level balance sheet losses (i.e., direct but uninsured damages and property value decreases) at individual residential properties after a significant flood event; (2) estimation of financial risk exposure of property owners, lenders, and local governments; and (3) classification of the distribution of these risks across geographic and economic groups throughout the flood-prone study area of eastern North Carolina. This approach utilizes a series of geospatial and stochastic models to improve understanding of how systemic financial risk could arise from flood impacts to residential properties. As such, this work illustrates a more nuanced approach to evaluating flood-induced financial vulnerabilities, providing new information that may inform planning for more effective recovery and resilience efforts in the future.

1.1 Background: Cascading Financial Risk

The process of financial risk generation at flood-affected residential properties begins with recognition of the multiple financial hurdles faced by property owners after an event. If the property is insured, direct damages may be fully covered, typically by the federal government's National Flood Insurance Program (NFIP). Rates of insurance purchase, however, are low (see Supporting Information (SI) for further discussion of the NFIP), and uninsured damage from major floods often represents the majority of total damage (Bradt et al., 2021; Dixon et al., 2006). For Hurricanes Florence and Harvey, two large flood events in the southeastern United States, uninsured damage accounted for over 70% of the total flood damage from the events (CoreLogic, 2017; RMS, 2018). Uninsured losses are often assumed to be borne by property owners alone (Government Accountability Office, 2017; Knowles & Kunreuther, 2014; Sheldon & Zhan, 2019), and while this is true to some degree, this assumption overlooks important cascading effects. The distinguishing feature of this research is the attempt to quantify the flood-related financial risk that groups beyond the property owners themselves face as a result of uninsured losses.

Most uninsured residential property owners do not have the resources to fully pay for the repair of uninsured damages (FEMA, 2021a; Jacobsen et al., 2009), and thus they turn to one or more of several financing strategies. Financial assistance is sometimes available in the form of federal grants, but these typically provide minimal funding and often involve long waiting periods (Government Accountability Office, 2020) (see SI for further discussion). As a result, property owners often borrow funds to cover the damage, either from private lenders or through federally-subsidized programs (Chandra et al., 2016; FEMA, 2021b; Flavelle, 2021). With respect to the latter, low-interest disaster loans are offered from the Small Business Administration (SBA) to owners of damaged property in presidentially-declared disaster areas. These loans require collateral, if available (Lindsay & Webster, 2019). For many property owners, equity in the damaged property itself is the largest, and sometimes only, source of collateral (FEMA, 2021b).

Equity is the difference between the property's value and any outstanding mortgage balance. Therefore it is also important to note that flood events in certain circumstances negatively impact property values in flooded areas, sometimes even at undamaged properties (Atreya et al., 2013; Beltrán et al., 2018, 2019; Bin & Landry, 2013; Bin & Polasky, 2004; CoreLogic, 2021; Kousky, 2010; Peacock et al., 2015). Any significant reduction in property value as a result of flooding can lower property owners' equity at the exact time it is needed as a collateral to support flood recovery efforts. Uninsured damage and reductions in property value can both negatively impact property-level balance sheets, and potentially affect recovery decisions made after a flood. In cases of severe balance sheet losses, the combination of uninsured damage and reduction in property value can lead to a situation of "negative equity" (CoreLogic, 2018b), in which a mortgaged property's value falls below the outstanding mortgage balance. Such a situation is also commonly referred to as an "underwater mortgage", a condition strongly associated with increased likelihood of mortgage default (Anderson & Weinrobe, 1986; Elul et al., 2010; Wong et al., 2004).

Individual flood events have been broadly linked to increased rates of mortgage delinquency (a precursor to default), particularly in areas with lower levels of flood insurance purchase (Kousky, Palim, et al., 2020). For example, after Hurricane Harvey in 2017, the mortgage delinquency rate at flood damaged properties in Houston increased by 205% (CoreLogic, 2018b). After a flood, property owners may be encouraged to "strategically default" or walk away from the damaged property (Liao & Mulder, 2021) as negative equity reduces the incentive to borrow to repair damages (Melzer, 2017). Other factors associated with a flood event, such as loss of employment and income, may also force property owners to default on their mortgage (Jacobsen et al., 2009; Sarmiento & Miller, 2006). Quantification of the degree to which floods increase the risk of mortgage default has not been fully investigated.

Estimating flood-related increases in mortgage defaults is important as they represent a financial risk to lenders, who have recently begun to recognize the potential for risk creation at flood-affected properties (Department of Homeland Security, 2021; Federal Home Loan Banks, 2019; Freddie Mac, 2020; Ouazad et al., 2021). Following default, lenders may seek to recover the outstanding balance on a loan via foreclosure sales (DePillis, 2017; Liu, 2009; USAGov, 2021). However, if the foreclosed property has experienced both severe damage and a reduction in property value such that value of the damages exceed the value of the property, neither the owner nor the lender have the potential for financial gain and the property may be abandoned (GAO, 2010; White, 2015; Zhang, 2012). In such cases, the abandoned property typically becomes the financial responsibility of the local government, which must pay to either maintain the property, or demolish any damaged structures (Bass et al., 2005; Bieretz & Schilling, 2019).

These often unrecognized and unquantified cascading financial risks are the primary focus of this research, as they have the potential to impact both pre-event mitigation and post-event recovery efforts. The Federal Housing Finance Agency (FHFA) specifically acknowledged the importance of quantifying the exposure of federally regulated lending entities to the financial risks of natural disasters and that such quantification will require modernization of traditional risk modelling practices (FHFA, 2021). As damage repairs from flood events are often so dependent on the ability of property owners to borrow money, increased vulnerability of lending institutions to flood-related risk may negatively impact individual and collective recovery efforts. While elements of mortgage default risk have been modelled both exclusive (Aktekin et al., 2013; Bhattacharya et al., 2019; Popova et al., 2008) and inclusive (Ataei & Taherkhani, 2015) of flood impacts, the financial risks that lenders are exposed to due to flood-related mortgage defaults have not previously been quantified. With respect to the financial risks accruing to local governments as a result of abandoned properties, demolition costs alone, as considered in this analysis, can be substantial. Over 20,000 properties were estimated to be abandoned after Hurricane Katrina (Plyer et al., 2011). Using an average of $20,000 per per abandoned property (Paredes & Skidmore, 2017), $400 million would have been required for all Katrina-related demolitions. Increased levels of abandonment can also lead to reductions in property taxes, stressing the budgets of local governments that are already stretched in many places (BenDor et al., 2020; Gilmore et al., 2022). Despite the recognition of these risks to lenders and local government, efforts to quantify them, including any sort of data-driven methodology for doing so, have not been well developed.

2 Materials and Methods

This work combines several unique datasets to estimate balance sheet losses (i.e., uninsured damages and property value decreases) from Hurricane Florence (2018), pre-flood financial conditions, and resulting financial flood risks at highly resolved spatial and temporal scales in eastern North Carolina (NC), USA. Though applied to the period impacted by Hurricane Florence, these methods are broadly applicable to other geographic areas and flood events. The following sections provide background information on the study area (2.1), followed by an introduction to the model framework (2.2), and a description of the data utilized in the analysis (2.2.1). Each component of the framework is then described in detail (2.2.2–2.2.5).

The analysis considers both the financial losses and financial risks resulting from flooding at residential properties due to Hurricane Florence. Losses include both property-level insurance payouts and balance sheet losses (i.e., uninsured damage and property value decreases). Risks are described in terms of the impacts of property-level recovery decisions (i.e., mortgage default or abandonment) which are influenced by both the magnitude of balance sheet losses and pre-flood financial conditions at each property (Figure 1). These decisions are inherently difficult to track, and so while this model framework allows for determination of the potential financial exposure for each risk-holding group, the degree to which these risks are translated into additional losses is unclear. Therefore, a distinction is made between the dollar amounts associated with ‘losses’ and those associated with ‘risks’ throughout the analysis.

2.1 Study Area

Since 1980, NC has experienced more than 25 flood events incurring more than $1 billion in damages, ten of which have occurred since 2015 (NOAA, 2020). There are at least 300 miles of coastal shoreline, 12,000 miles of estuarine shoreline (NC Division of Coastal Management, 2012), and 37,000 miles of rivers across the entire state (National Wild and Scenic Rivers System, 2021), creating conditions ripe for coastal and fluvial flooding. In 2021, over 169,000 structures statewide were located within the Federal Emergency Management Agency’s (FEMA) Special Flood Hazard Area (SFHA), indicating substantial exposure to flood hazards (North Carolina Department of Information Technology, 2021). Flood insurance penetration in 2018 among the SFHA-located residential properties included in this study is less than 20%, implying that property owners have relatively little financial protection against flood damages.

This analysis examines the impact of Hurricane Florence on eastern NC, defined as the 41 counties in the NC coastal plain (Figure 2) (State Library of North Carolina, 2012). Eastern North Carolina’s low-lying plain contains major rivers such as the Tar, the Cape Fear, the Neuse, and the Lumber. The Tar and Neuse rivers drain into the Pamlico Sound, the largest along the east coast (Kemp, 2017). The 41-county area is substantially rural, with up to 100% of residents living in unincorporated areas in some eastern counties, compared to 43% of residents in unincorporated areas statewide (Cline, 2020). In the U.S., incorporated areas are defined as “a legal entity incorporated under state law to provide general-purpose governmental services to a concentration of population” (U.S. Census Bureau, 2017) and unincorporated areas as any location not designated as incorporated. Though lacking the structure of an incorporated municipality, unincorporated areas receive some support from county and state governments, which will be considered the “local government” stakeholders for unincorporated areas in this analysis. In 1974, the Coastal Area Management Act placed 20 of the counties in the region under a cooperative management plan with the state government, in order to protect natural resources at the coast (CAMA 1974).

Of the residential properties used in this analysis, 42.6% are in incorporated areas and 57.4% unincorporated; 40.4% are in CAMA-designated (hereafter referred to as coastal) counties and 59.6% are in non-CAMA (non-coastal) counties; 11.7% are in the SFHA and 88.3% are located outside of the SFHA. Though median annual household income in NC is $72,000, a quarter of the counties within the study region have estimated median annual household incomes less than $50,000, and only four exceed the state average (NC OSBM, 2018). These preexisting inequities in the study area may increase both vulnerability to flooding impacts and undermine recovery efforts after an event (Drakes et al., 2021; Tate et al., 2021; Wang & Sebastian, 2021).

Hurricane Florence made landfall as a Category 1 storm on the North Carolina coast at Wrightsville Beach, NC (Figure 2, red triangle) on September 14, 2018. Florence moved slowly west-southwest (towards the red star in Figure 2), and was downgraded to a tropical storm on September 15, and a tropical depression on September 16. Maximum storm surge levels were estimated between 8–11 feet (2.4 – 3.4 m) along the shores of the Neuse River, with post-storm modelling efforts placing the maximum surge of up to 11 feet (3.4m) north of New Bern in Craven County. Florence set a new State record for tropical storm rainfall of 35.93 inches (0.91 m) outside of Elizabethtown in Bladen County. Widespread fluvial flooding was observed across eastern North Carolina, with 22 US Geological Survey stream gages measuring the highest peak stages on record and 18 measuring the highest peak flows on record (Stewart & Berg, 2019). Across the entire state, inclusive of but not limited to the study area, Florence is reported to have caused over $3.4 billion in direct flood damages affecting more than 79,000 structures, including residential, non-residential, and public structures (North Carolina Department of Public Safety, 2018). Of these, at least 59,000 structures were estimated to have been un- or underinsured, suggesting that uninsured damage accounted for 75% of the structural damage from the event.

2.2 Model Framework

The analysis combines spatially continuous data on the local environment (e.g., impervious surface coverage, distance to waterbodies, and overland flow accumulation) and property characteristics (e.g., structure square footage, parcel square footage, year built, first floor elevation) with financial observations (e.g., insurance claims, property sale timeseries, and annual mortgage originations) through a series of models to yield a spatially and temporally complete estimation of financial variables at residential properties (Figure 3). Property-level NFIP policy and claims records allow for an assessment of damage at insured properties and a two-stage machine learning random forest model (Figure 3, I) (section 2.2.2) is trained on these data to estimate damage at uninsured properties. Property value changes are estimated from residential property sales data using hedonic price adjustments and time-dependent spatial interpolation (Figure 3, II) (section 2.2.3). Mortgage data, including loan-level originations and repayment histories, enables stochastic simulation of household-level mortgage balances which are combined with property value estimations to determine continuous loan-to-value ratios (Figure 3, III) (section 2.2.4). Property-level loan-to-value estimations are adjusted to reflect balance sheet loss estimates, and then used to assign risk to property owners, lenders, and local governments within an agent-based decision-tree model (Figure 3, IV) (section 2.2.5)

2.2.1 Data Collection—Anonymized individual NFIP claims and policy coverage are publicly available from OpenFEMA (FEMA, 2021c); however, this analysis uses an unredacted version of property-level records of NFIP policies and filed claims obtained from FEMA Region IV for the State of North Carolina. These data are available from 1974 to 2020, though for this analysis only data relevant to the study period of September 10–30, 2018 (dates surrounding Florence's landfall on September 14, 2018) are used. Over 15,000 claims were filed during this period, representing 95% of all claims filed between September 1 and December 31, 2018. Properties where claims were closed without payment are removed from the dataset. This filtered dataset serves as training and testing input to a two-stage random forest machine learning model used to estimate Florence-related damages to uninsured properties (model I).

Residential property sales data from 2013–2019 is sourced from ATTOM™ Data Solutions, a provider of nationwide real estate data with information on more than 155 million U.S. properties (ATTOM, 2021). Sales data is used within the spatial interpolation model to estimate property values before and after Hurricane Florence (model II). The sales data includes date of sale, location of property, and the transaction amount. Loan-level mortgage origination data from the Federal Financial Institution's Examination Council (FFIEC) are stochastically sampled at the census-tract level to create synthetic mortgage balances at individual properties (model III) that are then utilized within mortgage repayment model. These data are made available through the Home Mortgage Disclosure Act of 1975 (CFPB, 2021), and contain every new federally-backed mortgage issued in each year. These mortgages are identified by census tract for privacy purposes. Over 90% of national mortgages are federally-backed (GAO, 2021). Most home mortgages are repaid in full before the end of the loan term, and data on loan repayment histories are obtained from Fannie Mae's Single Family Loan Performance Dataset (Fannie Mae, 2022). These data represent a subset of mortgages owned by Fannie Mae and are used to develop stochastic repayment profiles for individual mortgage originations. The mortgage origination data from 2018–2020, is identified by census tract and includes loan amount, loan term length, loan to value ratio, and property value. From 1990–2017, the origination data includes only the loan amount, census tract, and the purchaser of the loan.

Continuous environmental variables are used to calculate sets of independent variables at each property, defined as a land parcel and the structures contained on that parcel. Structure-level characteristics (e.g., first floor elevation, foundation type, structure type, structure value, structure square footage, and year built) and parcel-level characteristics (FEMA-designated flood zone, parcel square footage) are both sourced from NC OneMap, a data service supported by the State of North Carolina (North Carolina Department of Information Technology, 2021). Hydrologically relevant environmental variables include property distance to coast and stream networks; impervious surface coverage; overland flow accumulation; and hydraulic soil conductivity (see SI section S2 for variable creation details). Structures co-located on a single parcel are aggregated so that analysis across all models is conducted at a property-scale that is consistent with NFIP data and property sales data. Properties are filtered to include a maximum of two separate living spaces on one parcel (e.g., a duplex); the analysis does not consider larger multi-family structures (e.g., apartments). Additional variables unavailable from NC OneMap are created for use within the spatial interpolation model, including the distance from each property to the respective county's courthouse (used as a proxy for proximity to the primary population center) and status as incorporated or unincorporated (a proxy for price differences in rural vs. municipal areas) as defined by the U.S. Census.

2.2.2 Flood Damage Model—Flood insurance claim data provides comprehensive information regarding flood damage, while uninsured damage goes largely unobserved, except through localized windshield surveys or similar "on the ground" techniques. To estimate event-specific damage at uninsured properties across the study area, a two-step random forest model is utilized. Random forest machine learning algorithms have been successfully used to model flood hazards at multiple scales (Band et al., 2020; Collins et al., 2022; Kim & Kim, 2020; Woznicki et al., 2019) and estimate damages (Alipour et al., 2020), with several studies including flood insurance claims as reliable indicators of flood extent (Knighton et al., 2020; Mobley et al., 2020). The analysis described here builds on this body of previous research by utilizing flood insurance data to predict flood damage from a specific event at uninsured properties.

At each property, a set of variables describing specific property characteristics and the surrounding environment are used to predict the presence of flooding (Step 1) and magnitude of damage (Step 2). A review of prior studies utilizing random forest methods to predict flood hazards informed the selection of the independent variables included during the model training process. An initial set of 19 variables is pruned to a set of 13 variables (Table S1, signified with "I") to minimize input to the model without sacrificing performance by excluding variables from model runs one at a time, and discarding from the final set if the exclusion had minimal effect on model performance. The classification model utilized 7 of these variables (distance to coast, distance to nearest stream, first floor elevation, soil porosity (two characteristics), surrounding impervious surfaces (two spatial scales)). The regression model included 12 variables, 6 overlapping with the classification model (distance to coast, distance to nearest stream, first floor elevation, soil porosity (one characteristic), surrounding impervious surfaces (two spatial scales) and 6 distinct (flow accumulation, foundation type, heated square footage, surrounding impervious surfaces (one additional spatial scale), tax-assessed building value, year built).

The two-step random forest model is trained and tested with NFIP policy and claims data, and the selected environmental and property variables, to predict flood damages at uninsured properties. All calculations are performed using the scikit-learn package (version 0.24.2) within Python (version 3.9.7). In the classification model (step one), properties are split into two groups: (1) insured properties with an active NFIP policy in place and/or claim related to Hurricane Florence and (2) uninsured properties without a NFIP policy/claim during that period. Flood insurance policies are geocoded from provided addresses using 'rooftop' matches from the Google Maps API at an acceptable match rate of 89% (Zandbergen, 2009). The insured property dataset is then used as a training set to classify property as flooded (properties with claims) or not flooded (properties with *only* policies and no claims). The NFIP policy dataset provides the ability to use flood absence properties when training the random forest model, as the record includes properties with a policy but no claim after Hurricane Florence. Provision of absence locations is a necessary component to enable the classification model to "learn" the difference between flooded and unflooded properties. The increased certainty of flood presence and absence as described by NFIP policies and claims provides a unique modeling advantage, as machine learning classification research is often forced to generate ‘pseudo-absences’ in lieu of observed absence locations (Barbet-Massin et al., 2012; Mobley et al., 2020).

The classification model is calibrated using a stratified 10-kfold cross-validation procedure, repeating the model training 10 times, each time using 90% of the insured dataset to train and withholding 10% of the insured dataset to test the prediction results (Kohavi, 1995). The model utilizes adjustments for imbalanced classification (i.e., more unflooded than flooded insured properties), and hyperparameters tuned to 500 trees and a maximum depth of 15 nodes per tree. These hyperparameters are chosen to maximize the rate of successful classification, measured as the area under the receiver operating characteristic (ROC) curve (AUC), with reliability of the model increasing as the AUC approaches 1.0 (Bradley, 1997). The AUC scores from each model run are compared to ensure that results remained stable despite random selection of the testing and training sets. After model calibration, the classification model was highly sensitive with an acceptable AUC of 0.915 (±0.0054) (Hosmer et al., 2013).

In the training set, flooded properties are assigned a value of 1 and non-flooded properties a value of 0. The calibrated classification model returns a value between 0.0 and 1.0 at each uninsured property, which is used as a measure of likelihood that the property was flooded. A threshold value between 0 and 1 is then set, above which properties are classified as flooded and below which as not flooded. The choice of threshold represents a tradeoff between capturing true positives and excluding false positives. Methods exist to optimize this tradeoff, such as calculation of a geometric mean, the product of sensitivity (true positive rate) and specificity (one minus the false positive rate) at each threshold, followed by selection of the threshold with the highest geometric mean (He & Ma, 2013). However, the optimal threshold for the training set, consisting entirely of properties with NFIP policies, may not be the best threshold to categorize uninsured properties. Purchase of insurance policies is partially self-selecting, and likely biased towards properties with a history of flooding, as well as affected by purchaser characteristics, including individual risk preference, education, and income-level (Bradt et al., 2021; Petrolia et al., 2013). To the extent that there are unobserved differences between properties covered by flood insurance policies and those that are not (e.g., poorly maintained stormwater infrastructure in certain neighborhoods), the thresholds identified may have different tradeoffs between true and false positives when applied to uninsured properties. The threshold optimized by geometric mean (0.41) results in an overestimation of the proportion of damage that is uninsured when compared to overall damage estimates made by industry leaders such as RMS and CoreLogic (CoreLogic, 2017, 2018a; RMS, 2018). A more conservative threshold (0.69) would bring greater agreement between the model output and these industry estimates; however, this tightening introduces the possibility of a lower true positive rate while categorizing uninsured properties as ‘flooded.’

To determine if a more conservative threshold is appropriate for categorizing flooding in uninsured properties, the classification model results are compared to a set of observed property damages at a mix of insured and uninsured properties from on-the-ground “windshield surveys” conducted in New Bern, NC after Florence. The model performed well on these data, with an AUC of 0.867 (Figure 4). Additionally, the geometric mean of the New Bern testing set (0.68) was much closer to the conservative threshold (0.69) than the geometric mean threshold (0.41) of the original insured testing set. The threshold suggested via geometric mean of the insured testing set (represented by the blue marker in Figure 4), yields a much higher false positive rate on the New Bern testing set. This suggests that the classification model, trained on insured properties, predicts too much flooding when applied to all properties, possibly due to historically flood-prone properties being more likely to be insured and within the training dataset. These differences between insured and uninsured properties justify the application of a more restrictive threshold to uninsured properties.

In the second step, a RF regression model is trained using the group of properties with insurance claims (i.e., those with confirmed damages, a subset of the step one training set) to estimate damage in uninsured properties. This model is applied to all properties classified as “damaged” by the classification model; damages at all other properties are assumed to be zero. The degree of correlation (R^2) between predictions made with the calibrated model and observed values of flood damage within the insured claims testing set is equal to 0.48. Prior studies have discussed the difficulty of predicting damage even when using flood depth and extent, for example due to inconsistencies in deterministic depth-damage relationships (Freni et al., 2010; Wing et al., 2020). Probabilistic damage models represent an advance from depth-damage curves, but still face high levels of variability (Paprotny et al., 2021; Rözer et al., 2019; Wagenaar et al., 2017). Damage estimates can be particularly uncertain at the individual property level (Merz et al., 2004), and the regression model performs best in places with a high density of claim data creating a robust training set. The uninsured damage estimated in this analysis is more consistent with observed values when aggregated across the census tract or county scales (see Figure 5). In areas with relatively few insurance claims, the model does not predict damage as well, a result of insured flood damage in these areas being infrequent and largely due to idiosyncratic factors. The advantage of the RF model, despite these limitations, is that it is able to assess uninsured damage at many individual properties across a large spatial scale in an efficient manner, producing very accurate results at the census tract level.

2.2.3 Property Value Model—The impact of flood events on residential property values before and after Hurricane Florence is estimated using timeseries of property sales data. These data include the location of the property, and the sales price. Unlike property values derived from property tax assessments, which are only required to be re-evaluated every eight years (NC Department of Revenue, 2021), property sales data reflect real-time changes in market conditions, allowing for a more temporally reactive analysis of property values. Sale price data are observed at a small fraction of the total number of properties in any given time period, but these values can be interpolated across space and time to estimate property values at locations with no recent observations (i.e., sales). Since the residential housing stock is heterogeneous, sale prices are hedonically adjusted to control for implicit neighborhood characteristics before they are interpolated onto a neighboring property (Smith & Huang, 1995). A county-level multivariate linear regression uses available property-specific characteristics, including information about both the land parcel and the structures on it to estimate sales prices, such that:

$$\ln(o_\$) = \beta_1 * \ln(structure\ sqft) + \beta_2 * \ln(parcel\ sqft) + \beta_3 * year\ built + \beta_4 * incorporation\ status + \beta_5 * distance \tag{2.1}$$

where $o_\$$ is the observed property value;

and coefficients $\beta_1 - \beta_5$ to describe the county-specific relationships between the structure size, parcel size, year built, incorporation status (as a binary variable), and distance to the primary population center (i.e., county courthouse).

Using the coefficients from the regression and available property-specific variables, a hedonic property value ($h_\$$) is found for each property. The difference between the estimated hedonic price and the observed market sales price yields a "hedonic residual" (ΔH) such that:

$$\Delta H = \ln(o_\$) - \ln(h_\$) \tag{2.2}$$

The hedonic residual provides an estimate of the market value of the property relative to what is expected from the selected characteristics of the property. Because land often has locational or environmental amenities that are incorporated into property values, the hedonic residuals display strong spatial correlation (Milon et al., 1984).

The hedonic residuals at properties with no observed sales are interpolated using space-time kriging to generate best linear unbiased estimators based on the covariance of observed sales as a function of the time and distance between properties (Le & Zidek, 2006; Pyrcz & Deutsch, 2014; Waller & Gotway, 2004). By interpolating residuals from properties with observed sales onto properties without observed sales across a set of discrete quarterly timesteps, a timeseries of property value estimations can be generated at each property. The kriging process can be used to estimate the hedonic residual for any property, at any time, by calculating a weighted average of nearby observed sales. In space-time kriging, 'nearby' sales can be restricted to only properties that occurred on or before a given date, enabling the estimation of a time-series of values at any given property. Changes to the hedonic residual of spatially and temporally proximate property sales reflect changes in the location amenities at a given property. Similarly, the kriging process incorporates changes to a property's value caused by factors like recent flooding that may not be reflected in property-specific characteristics, but may be reflected in sale values.

The kriging model, adapted from (Johnson et al., 2019) estimates an expected value and variance at any particular point in time and space by capturing the variance in nearby (spatially and temporally) observed ΔH values and interpolating to unknown locations based on the statistical properties of the dataset as a whole. To fit the kriging model, semivariance values are first found for pairs of observed property sales that are separated by distance D and temporally by years T years:

$$sv_{D,T} = \frac{1}{2N_D}\sum_{1}^{N_D}(\Delta H_{d,t} - \Delta H_{d+D,t+T})^2 \tag{2.3}$$

where sv is the semivariance at spatial lag D and temporal lag T;

$\Delta H_{d,t}$ is the hedonic residual at spatial location d and temporal location t;

$\Delta H_{d+D,t+T}$ is the hedonic residual at any point within a spatial distance of d and temporal distance T from point $\Delta H_{d,t}$;

and N_D is the number of sales observations within a spatial distance of D and temporal distance T from point $\Delta H_{d,t}$

These values are found separately for incorporated and unincorporated properties within each county to account for the implicit differences in valuation of living in one area relative to the other (e.g., receiving municipal water and wastewater services) despite proximity of sales in time and/or space. Semivariance values are calculated for twenty equal sized bins for D values less than 1.5km. An adjusted covariance function uses a moving average of the semivariances such that the covariance between any two points can be found using:

$$C_{i,j} = \max(var_{all} - sv'_{D_{i,j},T_{i,j}},\ 0.0) \tag{2.4}$$

where, $C_{i,j}$ is the covariance between points i and j;

var_{all} is the variance of all property sales;

$D_{i,j}$ is the spatial distance between points i and j;

and $T_{i,j}$ is the temporal lag between points i and j

With the $sv_{D,T}$ values grouped across counties by incorporation status, semi variance functions are fitted at each time lag from 0–4 years with a piecewise linear regression. Additional counties adjacent to those in the study area are used to increase the number of data points for the model calibration.

Next, space/time kriging is performed to generate an estimation of all property values across the study region from 2013–2021, while maintaining observed values as datapoints. To estimate the value of the hedonic residual at a space/time point u, linear coefficients are calculated to formulate the point estimation as a weighted average of nearby space/time points. At a given property in the study region for a given quarter, the 16 nearest (spatially) sales observations up to 4 years prior are found. Using the semi variance functions corresponding to the observed temporal lag and incorporation status, a vector of kriging weights is found using:

$$w = \begin{bmatrix} C_{i,j} & \underline{1} \\ \underline{1}^T & 0 \end{bmatrix}^{-1} \begin{bmatrix} C_{i,u} \\ 1 \end{bmatrix} \quad (2.5)$$

where, w is a matrix of kriging weights for each of the nearby points;

$C_{i,j}$ is a matrix of covariances among the positions of nearby points (i,j = 1:16);

$C_{i,u}$ is a column of covariances relating the position of nearby points to the position of estimation point u;

and $\underline{1}$ is a single column of ones with a row for each nearby point.

The expected value of the hedonic residual at properties lacking sales data, Δh_u, can then be modeled at each u via combination of these 16 nearest observations $(\Delta H_{D,T})$ and their respective kriging weights:

$$\Delta h_u = \sum_{i=1}^{N} (\Delta H_i * w_i) \quad (2.6)$$

The uncertainty of each expected value estimation can be expressed by using the kriging weights to calculate kriging variance at each estimation point u, such that:

$$\Delta v_u = var_{all} - \sum_{i=1}^{N+1} (C_{i,u} * w_i) \quad (2.7)$$

where, Δv_u is the estimate of the kriging variance;

$C_{i,u}$ is the covariance between the estimation points and nearby observations;

and w_i is the kriging weights calculated in Eqn 1.5.

Kriging estimates of the hedonic residuals are estimated at each property at quarterly (3 month) intervals from 2013 – 2020. Using the regression coefficients from equation 1.1, the hedonic residuals are then converted into a property value estimate. At each space/time estimation point u, the kriging expected value (Δh) and variance (Δv) imply a random variable representing the property value at a given location and time. This analysis is concerned with the change in property value with respect to time, and properties with a large kriging variance may experience large changes in expected value from one timestep to another due to a relatively small change in the underlying observations. To reduce the impact of ‘noise’ in the kriged expected values on estimated property value changes, another source of property value data is incorporated, one that can be represented as a random variable. The set of all mortgages originated by major lenders, collected by the FFIEC provides this second source of data. These mortgages are anonymized so that they cannot be tied to individual properties, but they contain data on the census tract of the mortgaged property. A distribution of property values can be defined for each census tract based on the mortgage amount and loan-to-value ratio at mortgage origination. Probability distributions created from the kriged expected value and variance can be combined with the census tract level distribution to create an integrated distribution, such that:

$$P(iPV = \ln(x)) = \frac{P(kPV = \ln(x))*P(mPV = \ln(x))}{\sum_x P(kPV = \ln(x))*P(mPV = \ln(x))} \tag{2.8}$$

where, iPV is the integrated property value;

kPV is the kriging property value estimation;

and mPV is the mortgage origination property value distribution

At each location, a final property value is estimated using the median value of the resulting integrated property value distribution. The integrated estimates reduce the error between property value estimation and property sales observations at a subsequent timestep when compared with the hedonic property value estimations alone (Figure 6). The integrated property value estimates (orange) have a larger share of properties falling within a smaller error tolerance, indicating that the integrated method is an improvement over using the hedonic model (blue) alone (see SI section S3).

Changes in property value (Eqn. 2.9) are determined by the difference between the average interpolated value in the four quarters immediately "before" (v_{before}) and the four quarters beginning one year "after" (v_{after}) Florence. The "after" period is chosen to begin one year following Florence so that enough post-Florence property value observations are available to make robust property value estimations. Property value estimations during the quarter in which Florence occurred (Q3 2018) are excluded from these calculations:

$$\Delta Property\ Value = v_{before} - v_{after} \tag{2.9}$$

2.2.4 Mortgage Repayment Model—

Property value changes are important in the aftermath of a flood because the changes impact owner equity in a property, with equity calculated as the difference between a property's market value and the remaining balance on the property's mortgage. If the market value of a property falls below the remaining balance on the associated mortgage, the property is considered to have "negative equity" (i.e., the owners owe more on the mortgage than the property is worth), a condition associated with increased risk of mortgage default (Elul et al., 2010; Wong et al., 2004). These changes in property value, importantly, do not affect the remaining balance on a mortgage loan. The loan-to-value ratio (LTV) at a property serves as an indicator of increased mortgage default risk, with an LTV >1 indicating a situation of negative equity (Eqn 2.10).

$$LTV_T = \frac{b_T}{v_T} \tag{2.10}$$

where LTV_T is the loan-to-value ratio at any time T;

b_T is the loan balance at time;

and v_T is the property value at any time T.

The LTV ratio typically declines over time at individual properties as the balance on a mortgage is paid down; it can also change if the value of the property changes, for example, due to a flood event. In this analysis, post-Florence "adjusted" LTV ratios (aLTV) are calculated at individual properties by combining the expected property value with estimates of the remaining debt at the property, with debt including both the outstanding mortgage balances and uninsured damages (see section 2.2.5). An LTV (or aLTV) > 1 denotes a case of negative equity, increased mortgage default risk, and a creation of financial exposure for the property owner and the lender.

Annual, loan-level mortgage origination data from the FFIEC, covering the period 1990 – 2020, is used to establish initial mortgage balances and LTV ratio at newly purchased properties. For each mortgage originated between 1990 and 2018, we estimate the remaining balance at the time of Hurricane Florence (2018) using a constant repayment schedule based on the original balance, loan term, and interest rate, such that:

$$b_{T+1} = (1 + r_o) * b_T - \left(\frac{b_0 * r_o}{1 - (1 + r_o)^{-lt}}\right) \tag{2.11}$$

where, b_{T+1} is the mortgage balance ($) in the year following time T;

b_T is the mortgage balance at time T;

b_0 is the mortgage balance at origination;

r_o is the annual interest rate on the loan;

and lt is the loan term (years).

Most mortgages in the United States are repaid prior to the end of the loan term, either when the homeowner refinances their mortgage or sells the property. Although the mortgage origination data does not include information on early repayment, we can calculate the typical distribution of early repayment from historical loan performance data from Fannie Mae, a large purchaser of nationwide mortgages on the secondary market (Housing Finance Policy Center, 2021). This dataset samples a subset of single-family mortgages owned by Fannie Mae, each containing information about the duration of the mortgage before it was fully repaid. From this data a distribution of repayment times for single-family mortgages is sampled to create a 'repayment date' variable for each originated mortgage. Mortgage balances calculated in equation 2.11 are given a value of zero for all T greater than the sampled repayment date.

The initial property value associated with each mortgage origination can be estimated by multiplying the origination LTV ratio by the mortgage balance. However, mortgage origination data only contains original LTV ratios during recent years (2018–2020). For earlier years (1990–2017), only the original mortgage balance is contained in the data. To estimate original LTV ratios for mortgages originated before 2018, we create distributions of original LTV ratios from the 2018–2020 period, conditional on initial mortgage balance, the secondary market purchaser of the loan (Fannie Mae, Freddie Mac, Ginnie Mae, or other), and the loan classification as either for 'home purchase' or 'refinance'. Pre-2018 mortgage originations are assigned an LTV ratio based on the property's initial mortgage balance (adjusted to 2018-dollars using the North Carolina home price index), secondary purchaser, and home purchase/refinance classification. These sampled LTV ratios are then used to calculate an implied property value at each mortgage origination (eqn 2.10). The pre-Florence LTV ratios are calculated using the constant repayment schedule assumed in equation 2.11, and assuming property values appreciate through 2018 according to the North Carolina home price index, such that:

$$LTV_{2018} = \frac{b_{2018}}{\upsilon_{to} * \frac{HPI_{2018}}{HPI_{to}}} \tag{2.12}$$

where, LTV_{2018} is the loan-to-value ratio immediately before Florence;

υ_{to} is the implied property value at the time of mortgage origination;

HPI_{to} is the North Carolina home price index level at the time of mortgage origination;

HPI_{2018} is the North Carolina home price index level immediately before Hurricane Florence;

and b_{2018} is the mortgage balance immediately before Hurricane Florence in 2018, found using equation 2.11.

Mortgage origination data is anonymized and cannot be linked to individual properties, but each mortgage can be tied to a specific census tract. All mortgages with a non-zero LTV ratio immediately before Florence are assigned to individual properties within that census tract, without replacement. Originations are applied to properties where estimates of property values from section 2.2.3 are close in value to the property value implied from the original mortgage balance and LTV ratio, adjusted to 2018 prices using the North Carolina home price index.

The LTV ratios at each property are then used as inputs in the risk characterization model (Figure 2; Model IV). Although the simulated LTV ratios do not reflect the mortgage balance at any specific property, the stochastic process generates an accurate distribution of LTV ratios at a snapshot in time. There is excellent agreement between the modelled LTV ratios and LTV ratios observed in Fannie Mae's historical loan performance dataset (see SI section S4).

2.2.5 Risk Characterization Model—The outputs of the three models – uninsured damages (section 2.2.2), property values (section 2.2.3), and outstanding mortgage balances (section 2.2.4) – provide a comprehensive picture of property-level financial conditions and serve as inputs for the risk characterization model. The risk characterization model (Figure 3, Model IV) uses an agent-based decision tree and the datasets of financial variables (uninsured damage, property values, and LTV ratios) generated by the three constituent models of the framework to estimate how financial risk is distributed following a flood event. The agent-based decision tree model simulates financial conditions at the individual property level and uses a series of decision-making thresholds that estimate financial risk to property owners, mortgage lenders, and local governments. These risks are potential financial consequences that may accrue to risk holders due to interaction of balance sheet losses (i.e., uninsured damage and property value loss) with pre-storm property conditions (i.e., property value, equity, and mortgage balance). Insured damages are losses assumed by the federal government. Absent additional action, such as mortgage default, other flood-related losses of uninsured damage and property value are assumed by the property owner directly in the form of increased debt, adverse living conditions (i.e., living in a damaged property unable to make repairs) and loss of equity. The decision tree representing property owners' decisions is represented in Figure 7.

Just before the flooding event, the simulated LTV ratio and the interpolated, integrated property value provide an estimate of remaining mortgage balance (Eqn. 2.13) and owner equity (Eqn. 2.14). These provide measures of the property owner's ability to debt-finance repair of flood-related damages from either a private lender or most government programs (e.g., SBA disaster loans), using equity as collateral:

$$b = v * LTV_F \tag{2.13}$$

$$E = v - b \tag{2.14}$$

where LTV_F is the loan-to-value-ratio at time of Florence;

b is the loan balance at the time of Hurricane Florence;

v is the pre-Florence property value;

and E is pre-Florence the owner equity

An adjusted loan-to-value ratio is calculated by assuming that uninsured damages are fully repaired via borrowed funds, thus adding to the loan balance, and updating the property value to the post-event property value, based on the kriging results defined in Section 2.2.2:

$$aLTV = \frac{b + d}{v_F}$$

where aLTV is the adjusted loan-to-value-ratio after the flood;

b is the loan balance at the time of Hurricane Florence;

d is the value of uninsured flood damages to the property;

and v_F is the post-flood property value.

When aLTV> 1, the property owner risk is assumed to be limited to the pre-Florence owner equity (*E*). The lender is at risk of a loss equal to the sum of the property's uninsured damage (*d*) plus the outstanding mortgage balance (*b*) minus the post-event property value (v_F). This portion of the mortgage will not be recovered by the lender even if a foreclosure process is completed, or the property is sold "as is" to a third-party flipper. The lender risk is limited to the size of the property's mortgage; considerations of lost interest payments on the mortgage loan are not considered. If flood damage is so severe that it exceeds the post-flood property value, the lender is assumed to abandon the property, forfeiting the entirety of the property's remaining mortgage balance (*b*), and creating financial risk for the local government. In this case, the local government is assumed to demolish the structure at a cost of $20,000 per abandoned property (Paredes & Skidmore, 2017). It is important to remember that the financial quantities linked to default and abandonment estimates made via this procedure are, as defined earlier, risks as opposed to losses due to the uncertain nature of recovery decisions. Additional information linking property-level financial conditions to observed default or abandonment following Hurricane Florence could translate these risk estimates into loss estimates.

3 Results

Model outputs are stratified geographically and by governance areas to compare loss (3.1) and risk (3.2) distributions that may be relevant for flood resilience policy. This includes stratification by county as well as by presence inside or outside the SFHA; status as incorporated or unincorporated as defined by the U.S. Census Bureau; presence in a coastal versus non-coastal county, as defined by the North Carolina Coastal Area Management Act (CAMA). Illustration of total losses and additional financial risks, across what will be hereafter referred to as comparative groups, highlights unique vulnerabilities to flood impacts across spatially varying environmental, social, and political conditions. Additionally, these comparative groups are subject to different rules via CAMA regulations, local ordinances, and/or NFIP policies that influence each group's exposure and vulnerability to flood events. A higher level of detail (i.e., further stratification geographically) in the results is available in the SI (section s5).

3.1 Flood-related Losses

Total balance sheet and insured losses at residential properties across the study area equal $2.14B and are distributed among insured damage (17.1%), uninsured damage (49.4%), and property value loss (33.5%) (Figure 8). Out of a total of 876,284 residential properties across the study region, 38,345 are categorized as damaged through presence of a NFIP claim (9,310, accounting for $366M) or by the flood damage model (29,035, accounting for $1.06B). Damage at the property level (insured and uninsured) ranged from $13 to $534,409 per property, with a median of $27,798 and a 95th percentile of $98,345.

Roughly half of damaged properties (48.5%) experience property value loss, as do approximately half of the undamaged properties (46%). While some of this is likely the result of non-flood-related factors, previous research suggests that unflooded properties in close proximity to flooded properties also experience property value reductions (Kousky, 2010). Analysis of pre- and post-Florence periods indicate that median value of damaged properties decreased by $341 while median value of non-damaged properties increased by $848. Non-zero property value loss among damaged properties averaged $38,441with a median of $18,794, a 5th percentile of $1,314, a 95th percentile of $138,732, and a sum of $715.7M.

The federal government covered $366M in losses after Hurricane Florence via NFIP payouts. This was equivalent to 27% of all NFIP payouts made nationally in 2018 (Insurance Information Institute, 2020). Property owners are assumed to be responsible for balance sheet losses (i.e., uninsured damage and property value losses), although these could be partially mitigated by additional federal disaster relief programs, which are not considered here (see SI section S1), or via strategic default (see section 3.2). Balance sheet losses amount to $1.77B across the study area, with an average total loss per uninsured and damaged property of $61,027. Property level flood losses of this magnitude represent a substantial financial blow to most property owners, as this average loss represents 111% of the 2018 median household income ($54,602) in North Carolina (U.S. Census Bureau, 2019).

The relative sizes of the insured damage, uninsured damage, and property value losses vary across geographic and governance groups (Figure 9), as do the number of damaged structures in each group. Higher numbers of damaged structures are expected in coastal areas and the SFHA due to greater hazard exposure, and in unincorporated areas due to the larger number of damaged structures in rural areas.

Insured damage is higher in coastal areas and the SFHA, as would be expected with higher rates of flood insurance penetration in these areas (coastal: 2.3%, non-coastal: 0.3%; SFHA: 7.7%, non-SFHA: 0.2%). Insurance penetration was estimated within each comparative group using the number of active policies at the time of Hurricane Florence divided by the area’s total number of residential properties. Insured damage makes up similar proportions of total losses in unincorporated (15%) and incorporated areas (21%), but unincorporated areas experience higher insured losses than incorporated areas ($220M versus $146M). This is likely attributable to unincorporated areas comprising 57.4% of the study area and 66% of the damaged properties, as rates of insurance penetration in unincorporated areas (0.8%) are less than incorporated areas (10.9%) in this study region.

The combination of low insurance penetration and any large flood event causes substantial amounts of uninsured damage. More uninsured damage is predicted for coastal counties ($669M) than non-coastal counties ($386M), though uninsured damages still make up the majority of loss (65%) experienced by non-coastal counties. Unincorporated areas experience a significant amount of uninsured damage ($815M, 55%), both a higher magnitude of loss and a higher percentage of total losses than that estimated for incorporated areas ($240M, 35%). These differences can again be attributed to the larger number of unincorporated properties in the study region as well as the low insurance penetration in unincorporated areas. More uninsured damage is predicted outside the SFHA ($669M) than within it ($386M), consistent with previous assessments that conclude the extent of flood damage outside the SFHA is significant (Blessing et al., 2017; Brody et al., 2013; Highfield et al., 2013).

Property value decreases contribute over 20% to total loss across comparative groups. The high proportions of property value decreases as a fraction of total losses observed in coastal (37%) and incorporated (43%) areas are attributable to higher property values (Table 1), which may be a function of closer proximity to the coast, attractive features of larger urban communities, or provision of municipal services. These differences in property value have an impact on aggregated property value loss estimates, as losses of similar proportions (i.e., a 5% loss of pre-flood value) yield substantially different magnitudes of value decreases. Properties within the SFHA experience more property value decreases ($461M, 39%) than the non-SFHA properties ($254M, 25%). This is likely due to SFHA properties close proximity to desirable waterfront features such as riverfronts or beaches, as well as a stronger post-flood perception of increased flood risk within the SFHA (Atreya et al., 2013; Bin & Landry, 2013).

The financial impact of Hurricane Florence can be illustrated spatially with a bivariate distribution of uninsured damages and property value losses, aggregated by census tract (Figure 10). Uninsured damage is summed over the tract and property value loss is averaged over the total number of residential properties within each tract before stratification of both variables into tertiles (i.e., three equal-sized bins). Uninsured damage (red shaded inset map) is driven by both the flood hazard (i.e., total depth and extent of flooding) and the exposure of assets (i.e., the number and value of residential structures at risk), so damage is highest in populated areas most impacted by Florence. Property value losses (blue shaded inset map) were concentrated in the heavily damaged area as well, though some areas experienced high amounts of uninsured damage but only mild amounts of property value loss.

While magnitude of balance sheet losses is impactful to individual property owners, pre-flood property conditions (i.e., property value, equity, and mortgage balance) interact with these losses to increase the risk of mortgage default and abandonment. To further examine the impact of these mortgage-related variables on flood-related losses, results are stratified into property value quintiles and presented as losses (Fig 11, top) and losses normalized by pre-flood property value (Fig 11, bottom). The magnitude of insured damage and property value loss both increase with property value, while uninsured damage is similar across quintiles. When comparing property value quintiles in relative terms (i.e., normalized by pre-flood property value), however, the bottommost quintile experiences the highest proportion of uninsured damage. Uninsured damage greater than the original property value itself is expected, however, as cost of repairs for flood damage can often exceed pre-flood market value for lower valued properties (Moore, 2017).

3.2 Flood-related Financial Risks

If the value of aLTV > 1, a property is considered at risk of mortgage default. Similarly, if damage exceeds the value of a property (i.e., damage-to-value ratio > 1) a property is considered at risk of abandonment. These risks are represented in dollar terms as potential losses dependent on highly uncertain recovery decisions. Of the 38,345 damaged properties, 8,672 (22.6%) are at risk of mortgage default, and of those, 5,165 (13.5% of all damaged properties) are at risk of abandonment. The study region as a whole is exposed to $562M in financial risk associated with mortgage default and abandonment (Figure 12).

Property owners are exposed to 57.2% ($321.4M) of the flood-related financial risk, as property owners that default on their mortgage risk losing their investment (i.e., their equity). This risk to the property owner is present regardless of the fate of the property after mortgage default (i.e., if it is foreclosed and resold or abandoned by the lender). Across all properties at risk of default, the average equity at risk of being lost is $37,066, or 68% of the median income ($54,602) in North Carolina in 2018 (U.S. Census Bureau, 2019). Loss of this equity represents a significant potential financial blow to a property owner, as property equity is often a large portion of an individual's wealth (Fontinelle & Cetera, 2021).

Lenders across the study region are exposed to $137.4M in risk due to costs of repairing damage before reselling a defaulted property, loss of the 'underwater' portion of the mortgage that cannot be recovered through resale due to property value decrease, and forfeiture of any remaining mortgage balance upon abandonment. The potential impact of the flood is apparent when comparing rates of default risk among flood affected properties to the baseline risk present in larger mortgage loan samples. Among the flood damaged properties in this analysis, 22.6% had underwater mortgages (aLTV>1) compared to 3.7% of non-damaged properties, indicating the likelihood of much higher risk of default among damaged properties. However, not every underwater mortgage leads to a default. Historical loan performance data from Fannie Mae suggests that 90+ day delinquency rates (a proxy for default) increased from 0.5% to 1.2% following Hurricane Florence (Fannie Mae, 2022) (see SI Figure S4). Based on our estimates of 222,292 open mortgages in this study area (FFIEC, 2020), this translates into 1,319 defaulted properties (in addition to the pre-Florence background default rate), representing 15.2% of the 8,672 of damaged properties modelled with aLTV > 1. This result is in line with recent estimates made using historical Fannie Mae and Freddie Mac data (Schneider, 2020) which suggest that between 10–20% of underwater mortgages become 90+ days delinquent. If the properties identified here as having elevated default risk are representative of these observed defaults, this represents $20.9M in lender-realized losses from default. However, if the subset of observed defaults are sampled from the most deeply underwater of the at-risk properties, this would represent $24.9M in realized losses for lenders. As default rates can vary considerably even among property owners facing negative equity (Foote et al., 2008; Ganong & Noel, 2020), the realized loss estimates described here are not necessarily robust, and the risks quantified by the decision tree model are preferred for the remainder of the analysis. Importantly, underwater mortgages that have not defaulted (i.e., mortgages identified here as "at risk" of default) can potentially persist for years after the flood event while the remaining mortgage balance is being paid down, resulting in continued financial risk to lenders (Liu, 2009) and an inability for property owners to build equity.

Of the damaged properties, 13.5% are at risk of abandonment due to total damages exceeding property value, exposing local governments to $103.3M of risk due to potential demolishment costs. These flood-related risks represent 3.1% of the general expenditures county-level budgets (fiscal year 2017–2018) summed over the 41-county study region, though individual county budgets vary significantly (median: $55.7 M; range: $9.4M - $1.2B). The variability and limitations of these county-level budgets indicate that understanding elevated post-flood abandonment risk and the potential costs accruing to local governments may be significant, especially as distributions of risk across stakeholders vary considerably by county (Figure 13), even when aggregate risk (size of pies in Figure 13) across counties is similar.

For example, New Hanover (identified with “A”, Figure 13) and Robeson (“B” in Figure 13) counties experience similar magnitudes of financial risk: $17.7M and $15.2M, respectively. Property owners in each county are exposed to the most risk (64% in New Hanover; 55% in Robeson), but lenders are much more exposed in New Hanover (31%; $5.5M) compared to Robeson (15%; $2.3M). Conversely, local governments in New Hanover are only exposed to 4.9% ($0.88M) of risk, compared to 30% ($4.6M) in Robeson. Low property values in Robeson County relative to New Hanover (a pre-flood median of $66,195 and $159,333, respectively) led to damages that eclipsed post-flood property values in the former, generating higher risk of abandonment and therefore financial exposure for the local government in Robeson. Knowing that a damage-to-value ratio greater than 1 indicates risk of abandonment, Robeson County had 230 properties (0.62% of all damaged in county) exceeding this threshold, and New Hanover County had 44 properties (0.28% of all damaged). These differences highlight the need to consider the unique flood vulnerabilities in each county, as well as the resources each county has to recover, which are often a function of population, institutional capacity, and other county-specific characteristics (Jurjonas et al., 2020).

Using the comparative groups selected for this analysis to examine differential risk distributions suggests that experiences of financial risk arising from flood losses can change across political and geographic divides (Figure 14). Property owners are exposed to the most risk, with the fraction of risk relatively constant across all comparative groups. Lenders are exposed to higher risk ($107.7M) in coastal counties than inland ($29.7M), due to the intersection between high levels of total losses (property value loss and uninsured damage) and higher property values in coastal areas. A similar trend exists for incorporated ($37.3M) versus unincorporated areas ($100.1M). Conversely, lenders are exposed to slightly more risk outside of the SFHA ($79.8M) than inside ($57.6M), though property values are higher within the SFHA.

Exposure of local governments to flood-related financial risks from residential property abandonment are higher outside the SFHA ($67M) than inside ($36.3M). As most municipal groups include a mix of SFHA and non-SFHA properties, this effect may be negligible within a community, though it may be interesting for decision makers directing recovery and resilience efforts towards SFHA properties over those outside the SFHA. Local governments in coastal counties are exposed to a lower percentage of risk (16%) than in non-coastal counties (23%), however, the magnitude of the financial risk is higher in coastal counties ($66.6M vs. $36.7M). Even larger differences arise when comparing unincorporated and incorporated areas. Local governments responsible for unincorporated areas are exposed to 19% of risk ($82.3M) compared to 15% in incorporated areas ($21M). This difference is substantial as areas defined as unincorporated do not lie in a state-recognized area that is responsible for government support (U.S. Census Bureau, 2017), signaling that these areas may need assistance from larger entities, such as county, state, or federal government agencies to address the costs of abandonment. In combining comparative pairs with large discrepancies in risk magnitudes (i.e., coastal versus non-coastal, and incorporated versus unincorporated), the largest risk exposure exists for unincorporated communities in coastal counties ($50.9M) while the lowest risk exposure exists for non-coastal, incorporated communities ($5.3M). This further highlights the need to assess the impacts of flood-related financial vulnerabilities at more highly resolved scales.

The median value of damaged properties at risk of default is $50,665, compared to a median value of $116,399 at damaged properties that are not at risk of default. To examine the influence of pre-flood property values on financial risks, all individual uninsured properties are divided into quintiles by pre-flood property values and the highest and lowest quintiles are compared (Figure 15, a). Though both groups experience uninsured damages (Figure 15, b), lower valued properties are more sensitive to the additional debt resulting from these damages. This leads to more properties with an adjusted loan-to-value (aLTV) ratios over 1 (Figure 15, c), thereby resulting in increased risk of mortgage default and subsequent abandonment.

To further illustrate how financial conditions impact the distribution of risk across stakeholders, all properties (insured and uninsured) are again stratified by pre-flood property value into quintiles. When comparing financial risk (Figure 16, top), the risk exposure across all stakeholder groups rises significantly from $85M in the highest value quintile to $159M in the lowest quintile. This indicates that risks are increasingly generated by lower value properties. Additionally, the importance of abandonment risk becomes clear, as lender risk (gold) decreases with decreasing property value quintile, while local government risk (green) increases. This becomes even more clear when normalizing the risk generated at each property by pre-flood property value (Figure 16, bottom), as the lowest quintile generates the most risk exposure per dollar of property value. In fact, this normalized risk is more than twice that estimated in any other quintile. This discrepancy is a result of the higher property values in the upper quintiles that make the normalized value of financial risk significantly smaller than at low valued properties. As property values decrease, the distribution of normalized risk across stakeholders also shifts, with lower valued properties more at risk of abandonment, shifting financial risk to local governments. These results suggest that the bottom quintile of property owners is most at risk of mortgage default, and that when they do, this risk is more likely to be further transferred by lenders towards local governments via abandonment. Local governments must then shoulder the cost of demolishing these structures (as well as the costs of maintaining these properties, which is more difficult to estimate and not considered in this analysis).

4 Discussion

This analysis strongly suggests that flood damages at residential properties leads to financial risk that cascades beyond private property owners to mortgage lenders and local governments. In the case of Hurricane Florence, these three stakeholder groups were exposed to $562M in financial risk. Quantification of these systemic risks at a high spatial resolution can better inform community resilience policies through an understanding of the specific risk drivers (i.e., damage, property value loss, or preexisting property financial conditions). For example, lower value properties disproportionately generate financial risk for local governments, as uninsured damages more easily exceed the property's value than at higher value properties. Incentivizing purchase of federal flood insurance, particularly at low-value properties, via state or local government-supported insurance premium rebates could reduce this risk significantly, protecting property owners, lenders and local governments. Additionally, high-value homes represent the biggest source of risk for lenders, as they are likely to have large unpaid mortgage balances and can be subject to large reductions in property value. Federal regulations on borrowing that would lead to lowering initial LTV ratios (i.e., higher down payments) on high value properties at elevated risk for flooding could also reduce the likelihood of balance sheet losses that would result in negative equity and higher default and abandonment risk. In addition, property-level analyses identifying areas most vulnerable to post-event property value decreases could be used to target areas for post-flood buyouts or mortgage assistance, providing a stopgap for default and abandonment risk that would reduce risk for property owners as well as lenders and local governments.

Local governments are exposed to financial risk via property abandonment, for which low valued properties are particularly at risk, as balance sheet losses more easily exceeding a property's equity (default risk) as well as its value (abandonment risk). Property abandonment can have long term impacts on local governments beyond the demolition costs considered in this analysis, including property value depreciation, maintenance and rehabilitation costs, increased crime, and extended health impacts (Bass et al., 2005; Bureau of Governmental Research, 2008). Increased abandonment is associated with significant community outmigration (De Koning & Filatova, 2020; Plyer et al., 2011), leaving local governments facing decreased tax revenues (BenDor et al., 2020; Greer et al., 2021). These processes can shift the financial risk associated with abandonment at flood-affected properties to the community at large. Following a flood event, local governments may also struggle to provide basic services, make their debt payments, and maintain access to credit (Jerch et al., 2020), with their budgets further strained by increasingly high expenditures towards resilience-promoting measures, such as flood control infrastructure (Gilmore et al., 2022). Small and/or rural local governments are more limited in terms of personnel, resources, and the institutional capacity available to pursue pre-flood mitigation strategies post-disaster recovery funding (Jerolleman, 2020; National Association of Counties, 2019). With low mitigation capacity and high vulnerability to financial risk, flood impacts in rural areas may be absorbed by state or federal entities, and necessitate innovative and tailored solutions for resilience (Cutter et al., 2016; Seong et al., 2021). Financial risk characterizations such as those provided in this analysis can improve understanding of these uncertain community-level processes, and aid in selecting strategies to prevent excess flood-related abandonment and community decline.

Stakeholders focused on mitigating the impacts of flood events and reducing systemic risk should also be conscious of social equity implications across property value levels. Although high-value properties represent a large portion of the risk to lenders because individual defaults cause more nominal risk when mortgage balances are higher, low value properties have a much higher risk of both default and abandonment after a flood. This is consistent with findings that disasters can exacerbate existing financial inequalities (Chakraborty et al., 2019; Drakes et al., 2021; Emrich et al., 2019; Howell & Elliott, 2019; Katz, 2021; Peacock et al., 2015; Ratcliffe et al., 2020a; Roth Tran & Sheldon, 2019). Mortgage default can have a substantial effect on the financial standing of a property owner, impacting both their ability to recover from a flood event and their overall psychological and physical wellbeing (Alley et al., 2011; Vásquez-Vera et al., 2017). Moreover, property owners at risk of default and/or abandonment may be the least able to mitigate their personal financial risk through strategies such as purchase of flood insurance (Atreya et al., 2015; Brody et al., 2016; Kousky, 2011) or may be unable to access or qualify for SBA loans (Wilson et al., 2021). In these cases, property owners retain negative consequences of the flood, which may include living in a damaged home, or absorbing losses of equity. If property owners avoid default after a flood, but can borrow funds to repair the damages, they may retain significant levels of debt that can accumulate over time with successive flood events. Additionally, new borrowers within flood-affected areas have been observed to be less creditworthy and at higher risk of default, causing lenders to set higher interest rates on loans and be more likely to securitize those loans (Ratnadiwakara & Venugopal, 2020). These lender responses could constrict access to credit for borrowers within the lending pool, even those far outside the flood's footprint. Sensitivity to these sociodemographic feedback loops and the preexisting inequitable policies that compound them will be essential to reduce the resurrection of unjust lending practices (i.e., redlining) and act against climate gentrification (De Koning & Filatova, 2020; Keenan et al., 2018). Repetitive flooding in eastern North Carolina has been observed and is expected to increase (Kunkel et al., 2020), and so the compound effect of multiple floods in quick succession on individual and systemic financial risk may be substantial (Kick et al., 2011; OECD, 2016).

Further analysis is required to improve the risk estimates generated in this work, and to enable the translation of financial risk into realized losses, both of which will assist decision-makers in developing more targeted resilience strategies. Several assumptions are made in the modelling approach that introduce uncertainty in the results. First, the random forest model exhibits higher levels of uncertainty in uninsured damage estimations at the individual property scale (see end of Section 2.2.2). These uncertainties are similar to those of standard damage estimation methods (e.g., depth-damage models), though the difference between observed and modeled damage decreases in this analysis as the values are spatially aggregated. Second, estimates of property value via spatial interpolation (model II) are crucial to estimating risk, but exhibit some uncertainty at the individual property scale. Statistical noise within these estimates can be interpreted as real changes to property values, potentially exaggerating the magnitude of property value decrease at individual locations. Adjustments to property value estimates based on kriging variance estimates and census tract-specific mortgage data, reduces the impact of this statistical noise. Third, the risk characterization model relies on negative equity as the trigger for mortgage default risk. Though negative equity is a well-accepted predictor of default risk (Anderson & Weinrobe, 1986; Elul et al., 2010), there is research regarding the influence of other factors on the decision to default, including experiencing adverse life events (Foote et al., 2008; Ganong & Noel, 2020) and costs associated with defaulting (Krainer & Leroy, 2010).

Influences on individual decisions regarding mortgage default deserve additional research focus and may require the development of new methods and potential data sources, such community surveys used to assess related aspects of environmental health literacy (Gray, 2018). Fourth, there is substantial uncertainty in the magnitude of flood-related financial risk to local governments as, in this analysis, the expense of demolition is the only cost considered, even as the cost of maintaining abandoned properties can also be significant (Bass et al., 2005). Other risk creation mechanisms may be set in motion following a flood event, as local government tax revenues are strongly tied to long-term trends in property value appreciation. Foreclosure and property abandonment impact long-term property value changes (Immergluck & Smith, 2010; Sun et al., 2020), creating feedback loops for local governments that have proven difficult to address (Hackworth, 2016).

This analysis quantifies the potential flood-related financial risks that arise from Hurricane Florence in eastern North Carolina. The modelling framework, however, is intentionally structured to be applicable to other geographic locations and flood events of varying intensities, presuming sufficient data is available. The relationships between the flood hazard and the financial system (i.e., insurance, property and mortgage markets) examined here are influenced by several physical and socioeconomic factors, especially the preexisting condition of household-level debt. Results may vary if the overall health of this financial system was being negatively impacted (i.e., by a recession). Additionally, although this work presents novel methods to characterize flood-related risk among different stakeholder groups, the aggregate representation of lenders in this study simplifies the complex strategies that individual lenders use to hedge their financial risk with tools such as mortgage-backed securities. More work is needed to understand how uninsured damage and property value loss from flood events can lead to or exacerbate risks for investors and financial institutions with exposure to lending default risk. In future work, the methods described here could be straightforwardly adapted from an analysis of a single flood event to broader assessments of the compounding effects of repetitive floods or multihazards on financial risks and how they evolve over time. A better understanding of how a range of intermittent natural hazards can create long-term financial impacts for various stakeholders could have wide application in the climate resilience space.

5 Conclusion

Floods are expected to increase in frequency and intensity in the coming decades due to climate change, population growth, and increased development (Bates et al., 2020; Hallegatte et al., 2013; Marsooli et al., 2019; Wing et al., 2018). As such, the development of responsive strategies to mitigate the multifaceted financial impacts of flood events is of critical importance. Policy selection to address flood resilience is however complicated by the difficulties associated with predicting the extent of flooding, associated damages, accompanying indirect financial risks, and specific community vulnerability. This paper presents a novel framework for assessing flood-related balance sheet losses and developing estimates of the financial risks that arise in response to those losses. The findings provide new information on how flood-related losses and associated financial risks are distributed geospatially and across stakeholder groups, characterizing localized vulnerability to floods that could be mitigated through a suite of physical interventions and policy tools. This analysis illustrates how property-level recovery decisions (i.e., mortgage default and property abandonment) can create systemic financial risk, extending flood impacts to stakeholders and institutions located well outside the flood event's inundation footprint. Pending data availability, the modeling methodology developed here can be applied in other geographic locations and flood events to improve understanding of flood-related financial vulnerabilities beyond estimation of physical damages alone. Use of this type of approach in the analysis of a wide range of flood events and impacted areas should generate a better assessment of local and national flood-related risks. This will ultimately aid in the development of more effective and equitable strategies to improve community resilience to floods and other environmental hazards.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Key Points:

- Estimates of uninsured flood damage and property value decrease can be used to predict rates of mortgage default and abandonment
- Financial risk, previously not well quantified, thus expands beyond property owners and insurers to include lenders and local governments.
- A new analytical approach estimates $562M in financial risk from Hurricane Florence with disproportionate impact at low valued properties.

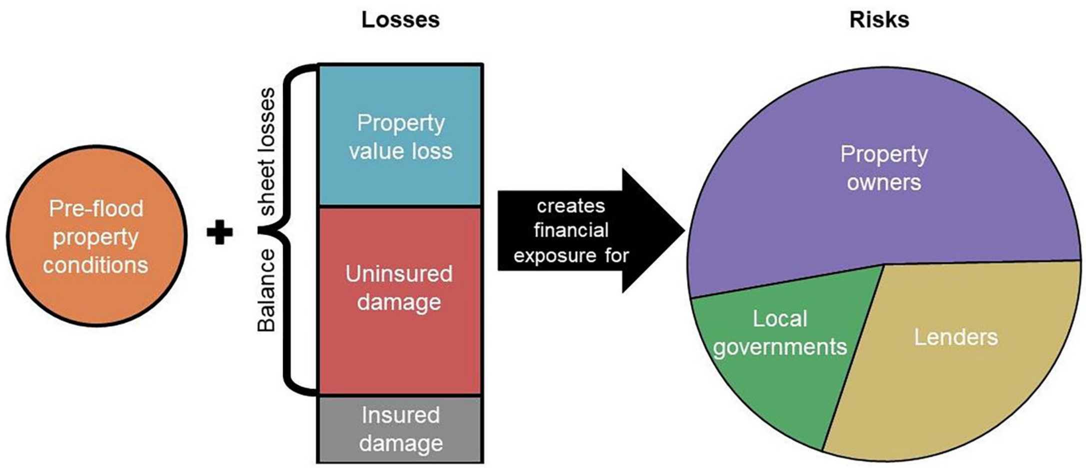

Figure 1.
Interaction of pre-flood property financial conditions (i.e., property value, equity, and mortgage balance) with balance sheet losses (i.e., uninsured damage and property value decrease) can increase the likelihood of mortgage default and abandonment to expose property owners, lenders, and local governments to financial risk.

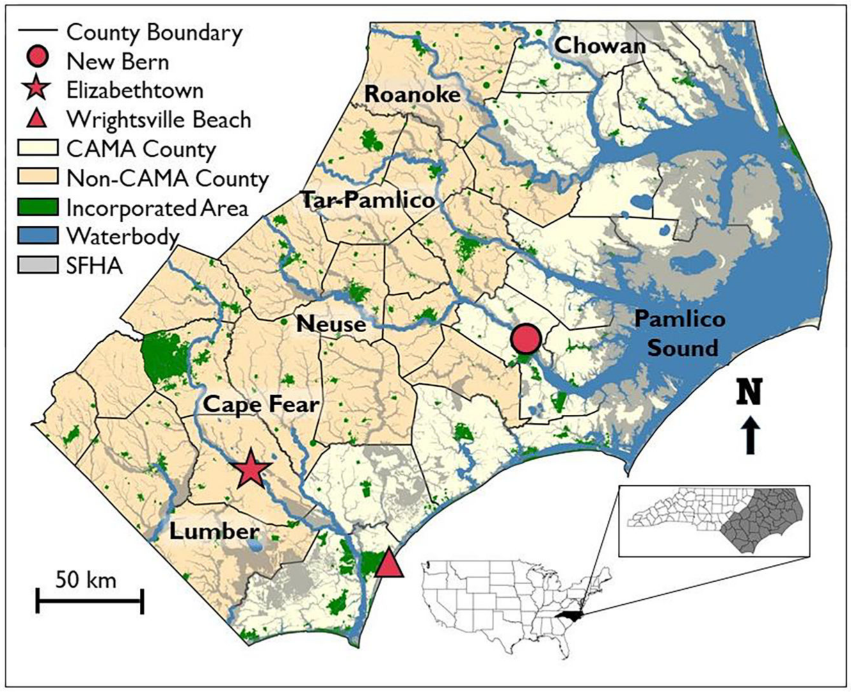

Figure 2.

The eastern North Carolina study region. Hurricane Florence made landfall at Wrightsville Beach, red triangle; highest storm surge occurred in New Bern, red circle; Elizabethtown, red star, set the state record for rainfall from a tropical storm. Coastal counties under the Coastal Area Management Act (CAMA) in light yellow, non-coastal (non-CAMA) in light orange.

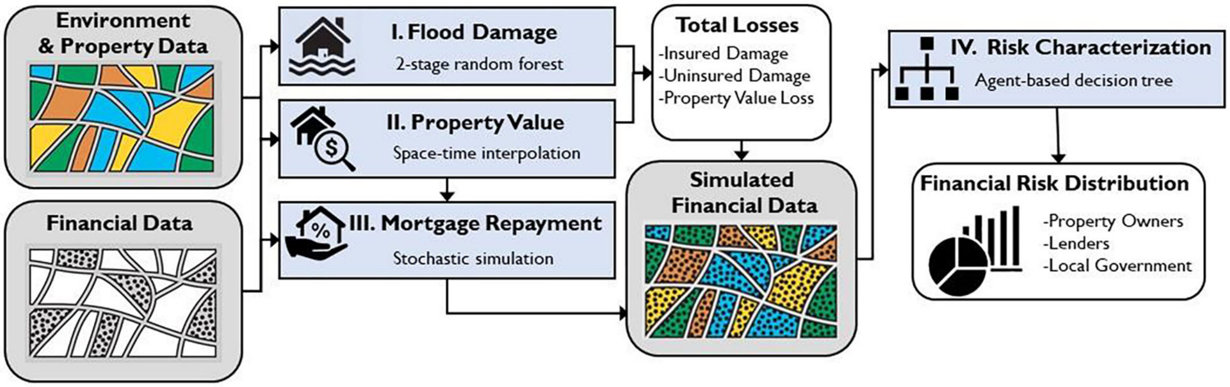

Figure 3.

Framework to estimate flood-related losses and assign financial risk. The leftmost grey boxes represent the available environmental, and property data (available for each property), as well as financial data (available at select properties, denoted by dotted fill).

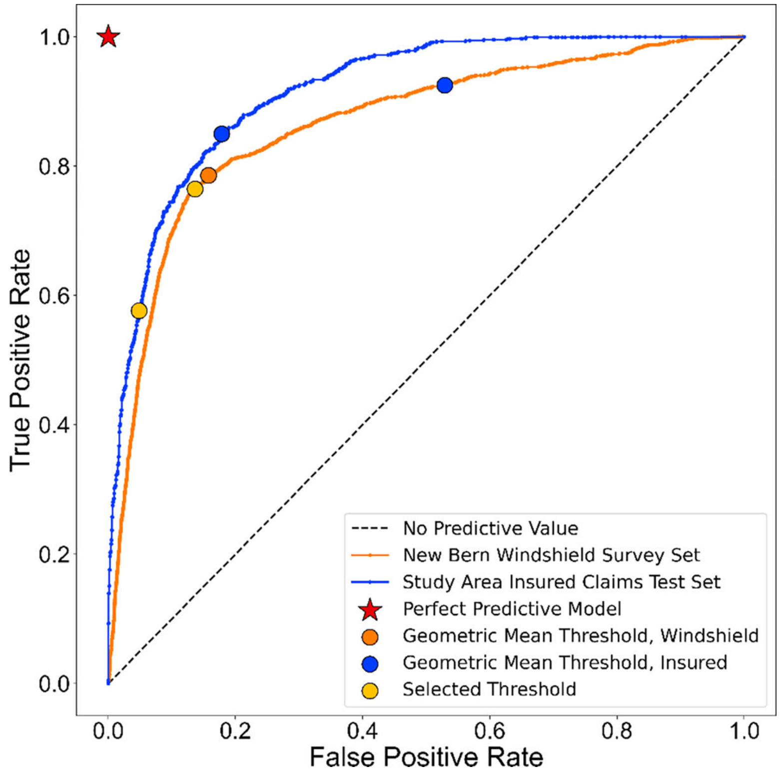

Figure 4.

Performance of the classification random forest model (step 1) on both the insured dataset and the windshield data. Use of the selected threshold (yellow marker) on the windshield survey set balances true and false positives more effectively than the insured dataset's geometric mean threshold (blue marker). The most stringent threshold is near the origin (above which nothing would be classified as flooded), while the most relaxed threshold (above which everything would be classified as flooded) is in the upper right corner.

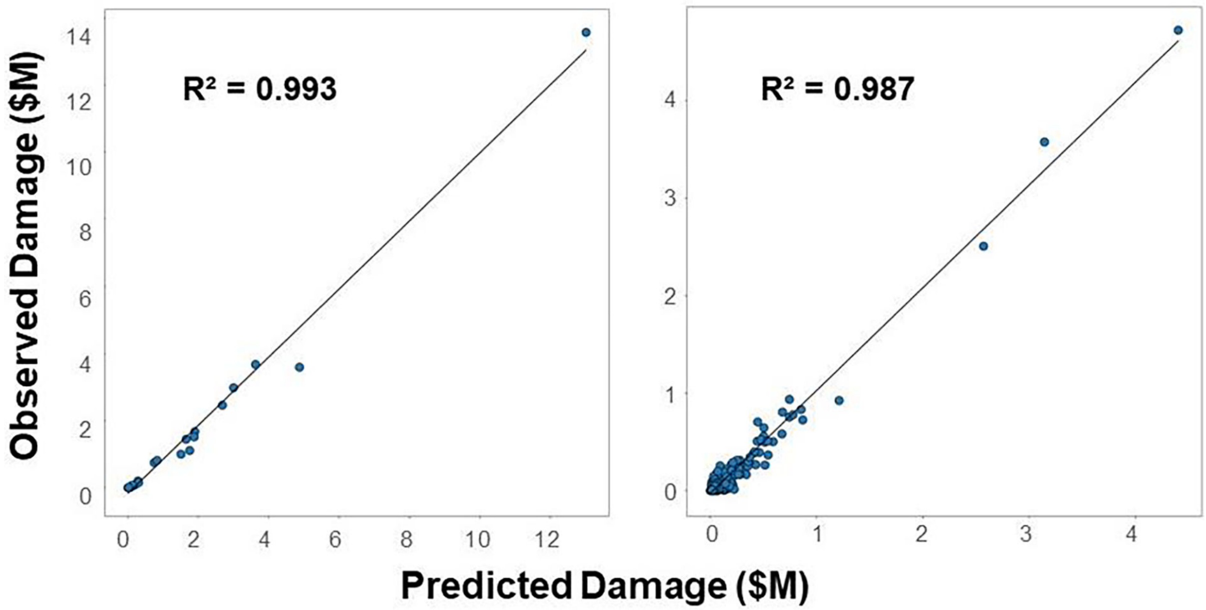

Figure 5:

Observed damage amounts versus damage predicted by the random forest regression model, aggregated to the census tract (right) and county (left) scale.

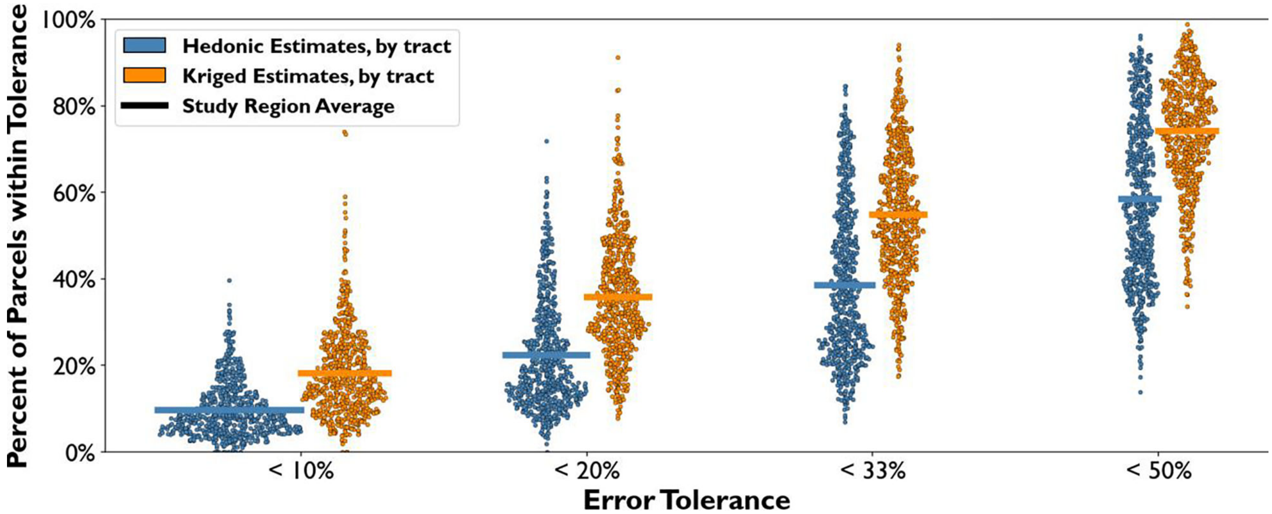

Figure 6.

Percent of parcel-level property value estimations falling within a certain error tolerance of subsequent observed transaction values and the integrated property value estimates (orange), as well as observed sales and hedonic estimates (blue).

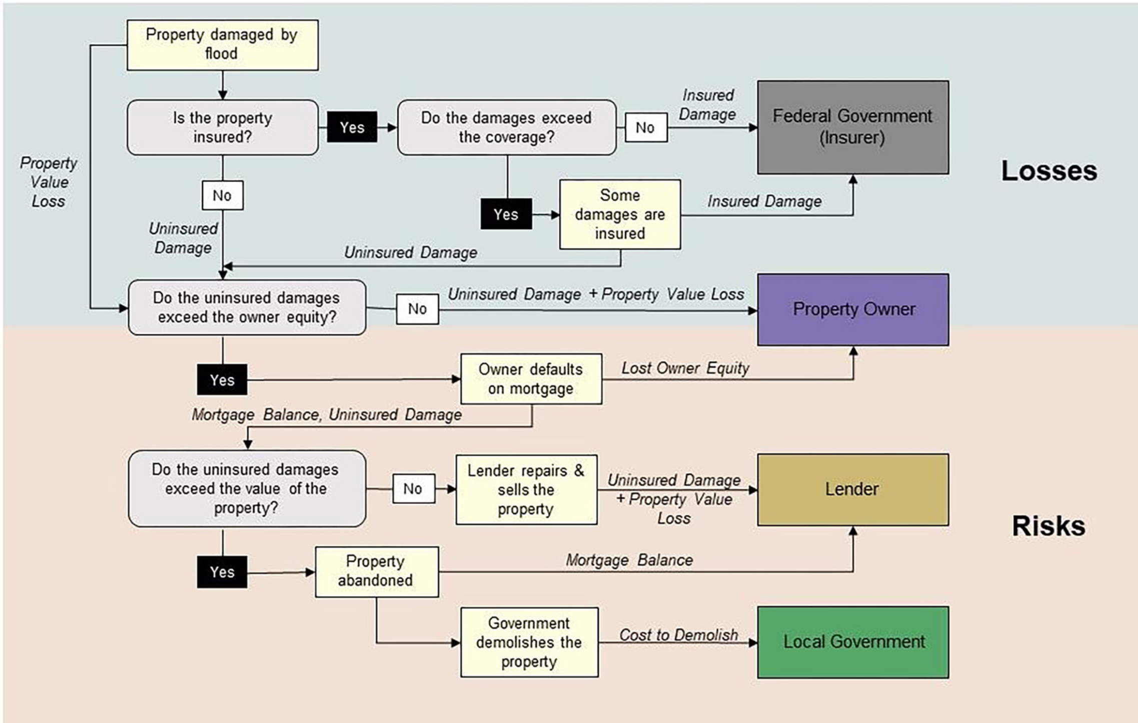

Figure 7.

Losses (insured and balance sheet), shaded gray, interact with pre-flood property conditions to estimate financial risks, shaded beige, to three risk holding groups (property owners, lenders, and local governments) via a decision tree. Decision nodes shown in light gray; choices shown in black (yes) and white (no); and resulting actions from decision nodes in pale yellow. Amounts of loss and risk flowing through the decision tree are specified in italics.

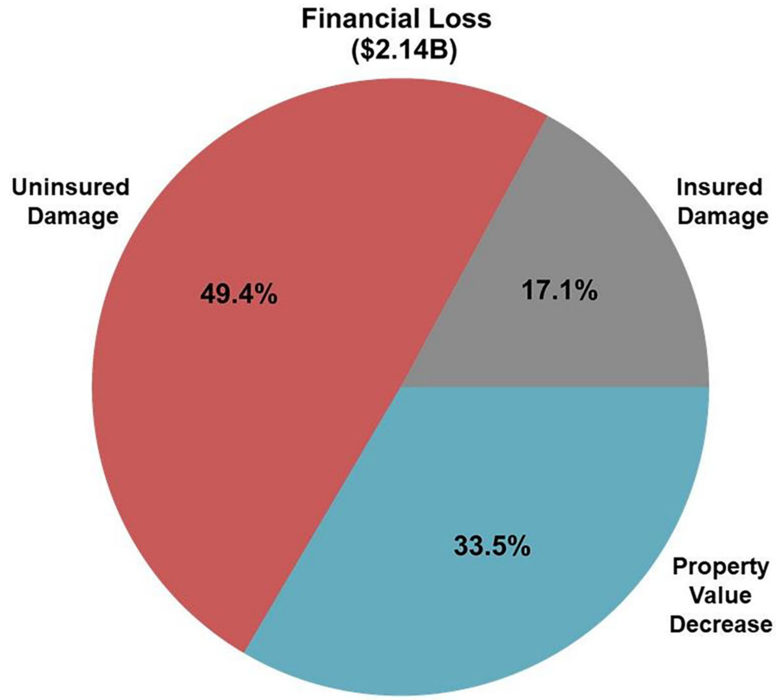

Figure 8:

Losses due to flooding from Hurricane Florence across the study area.

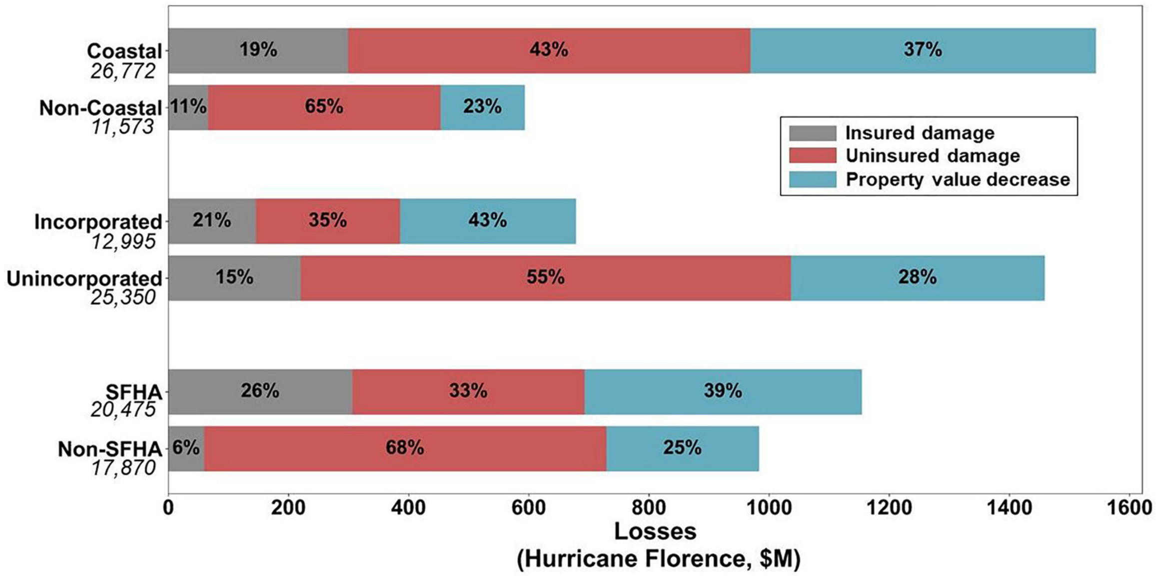

Figure 9.

Estimates for insured damage (grey), uninsured damage (red) and property value decrease (blue) across comparative groups with proportion of loss within group shown on respective portion of bar. Number of damaged properties within each group is italicized beneath the group name. Note, bars should only be compared within appropriate pairs (e.g., SFHA to non-SFHA) and not across pairs (e.g., coastal to SFHA) as groups across pairs are non-exclusive.

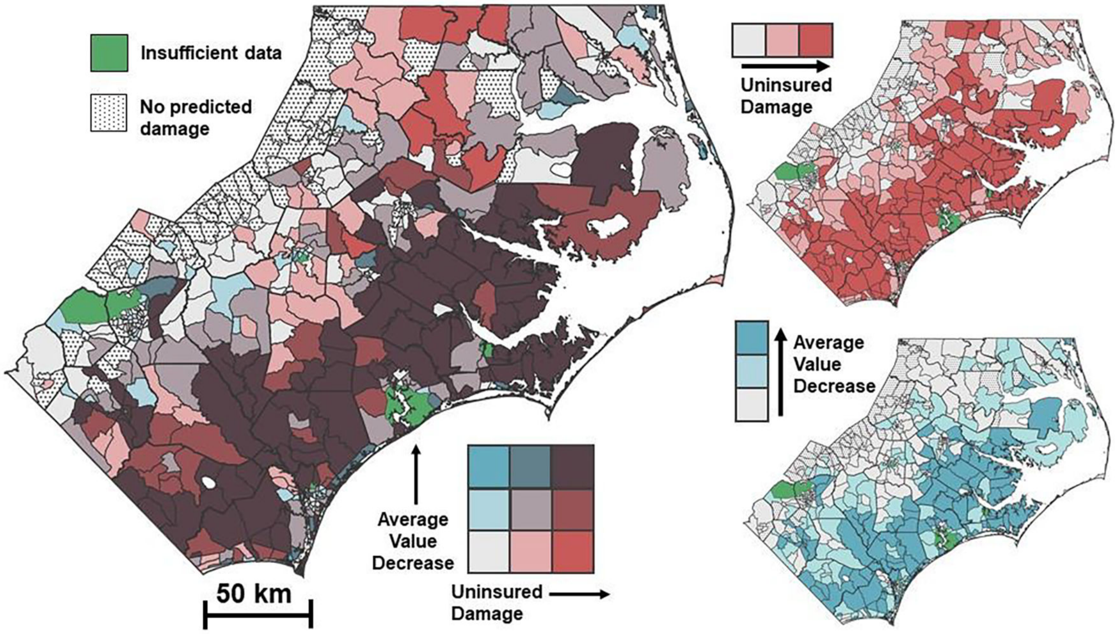

Figure 10.

Census tract level uninsured damage and average property value loss. The top tertile for each variable (most damage, most property value loss) is represented by the dark maroon color. Monovariate maps, right, isolate measures of uninsured damage (red) and average property value loss (blue).

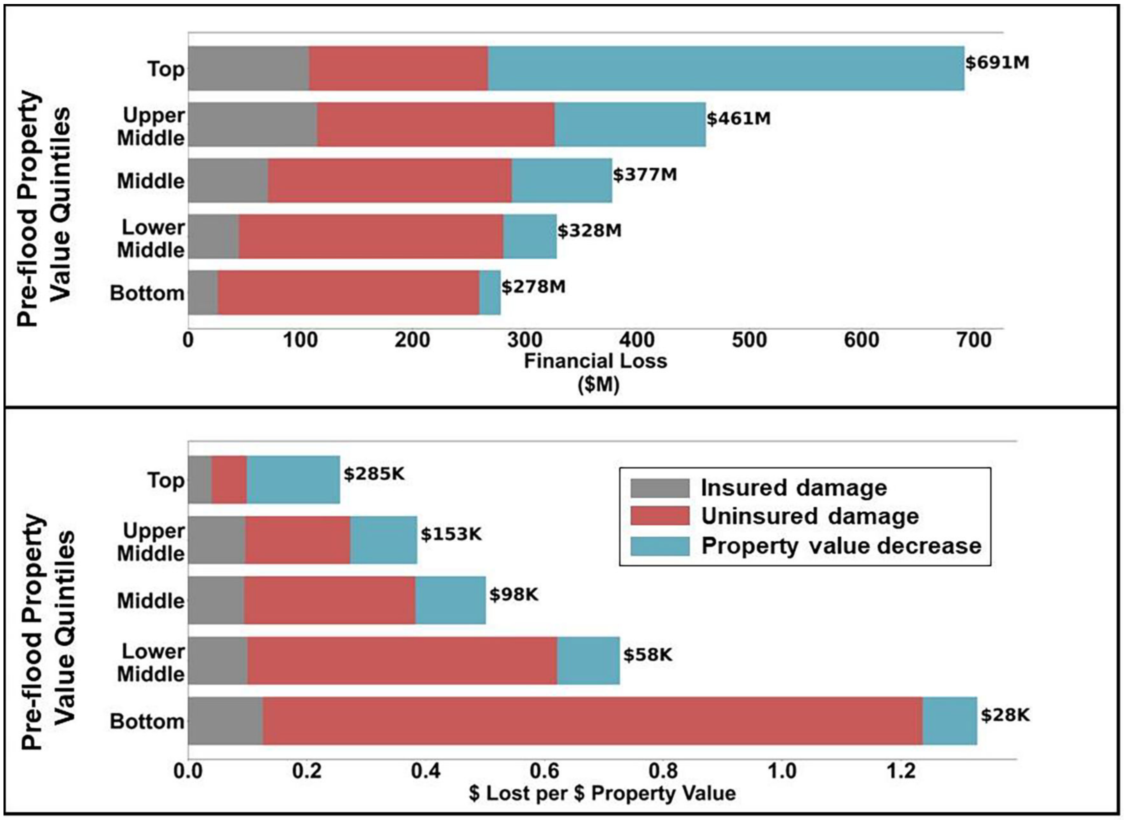

Figure 11.

Total (insured and balance sheet) loss (top) and total loss normalized by preflood property value (bottom).

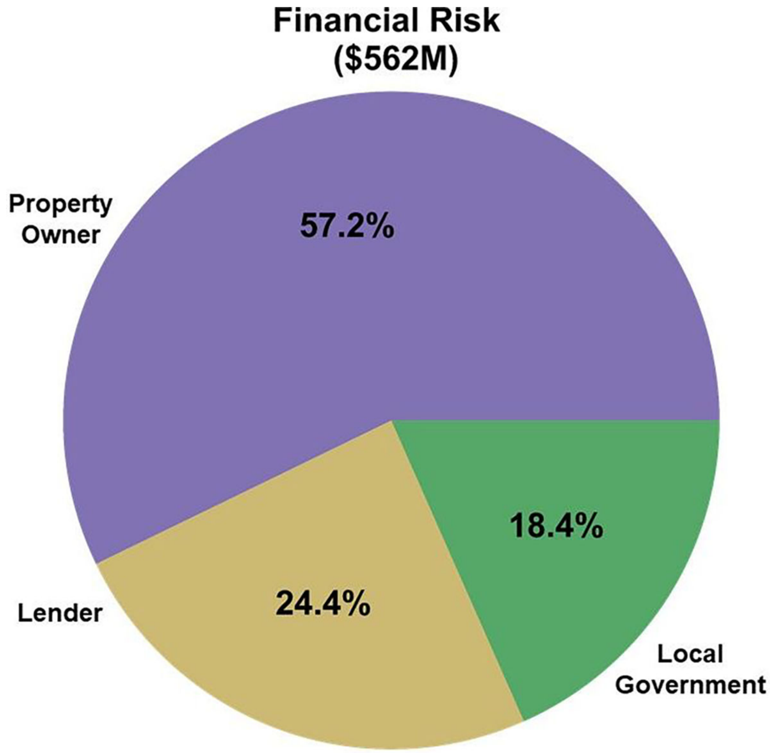

Figure 12:
Total financial risk associated with mortgage default and property abandonment

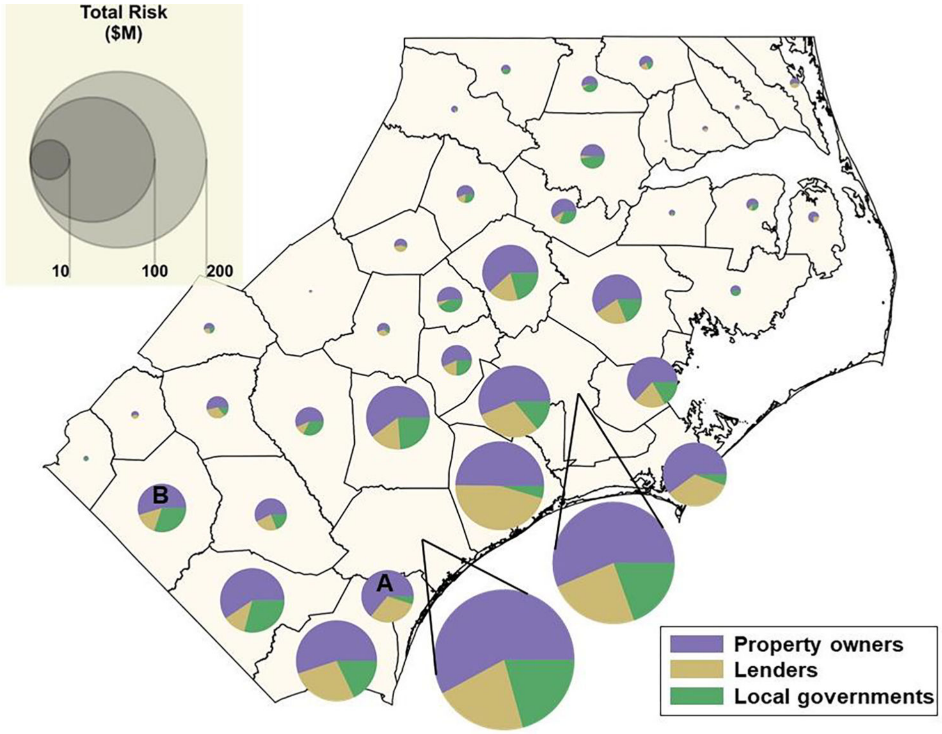

Figure 13.

County-by-county risk distributions with magnitude of total county risk represented by size of pie chart (see inset).

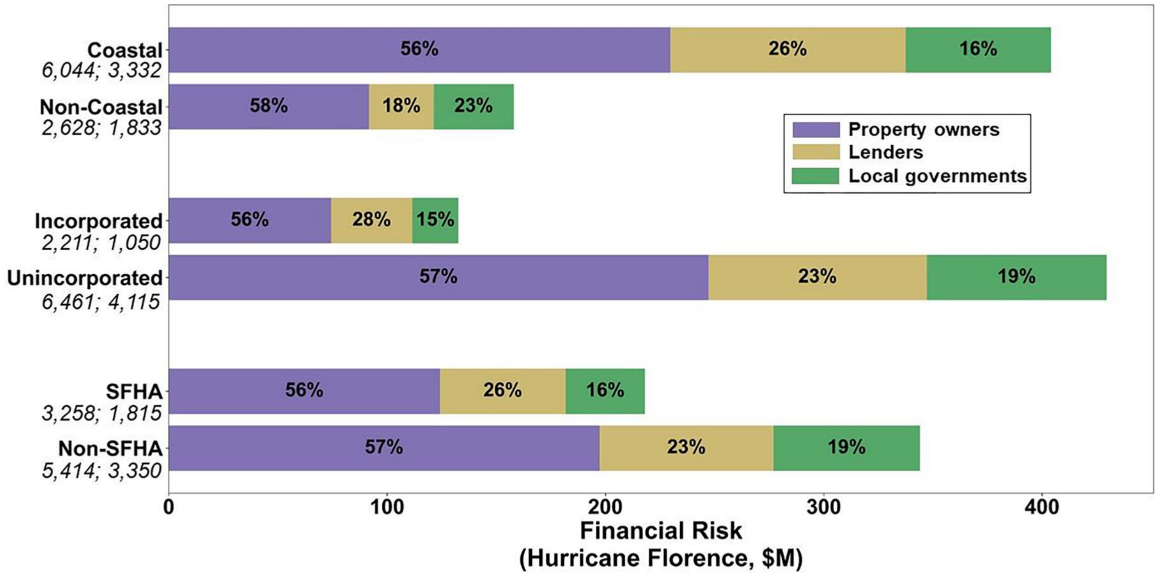

Figure 14.

Distribution of flood-related financial risk across comparative groups (sum of risk over each pair is the same, $562M). Number of properties at risk of default within each group is italicized beneath the group name, followed by the number of properties at risk of abandonment. Note, bars should only be compared within appropriate pairs (e.g., SFHA to non-SFHA) and not across pairs (e.g., coastal to SFHA).

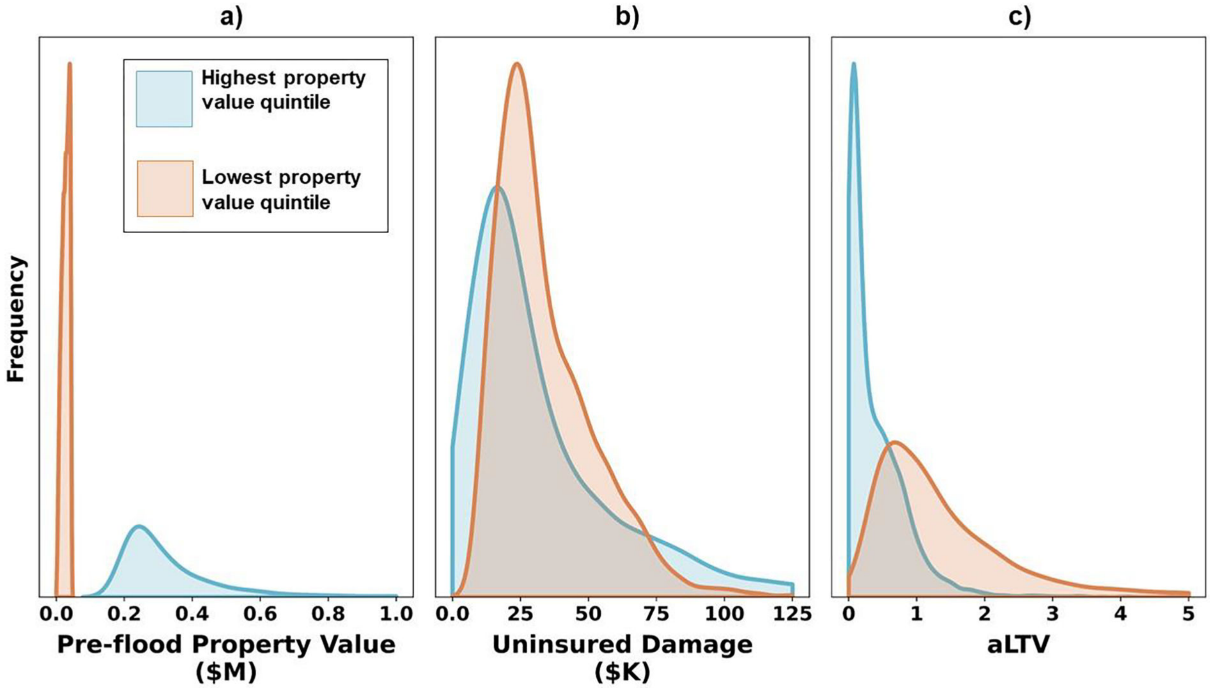

Figure 15.

Comparison between the distribution of property values for uninsured properties comparing the highest pre-flood property value quintile (blue) and the lowest pre-flood property value quintile (orange). Lower value homes ('blue') experience more damage relative to their property value, leading to higher adjusted loan-to-value (aLTV) ratios and increased probability of default.

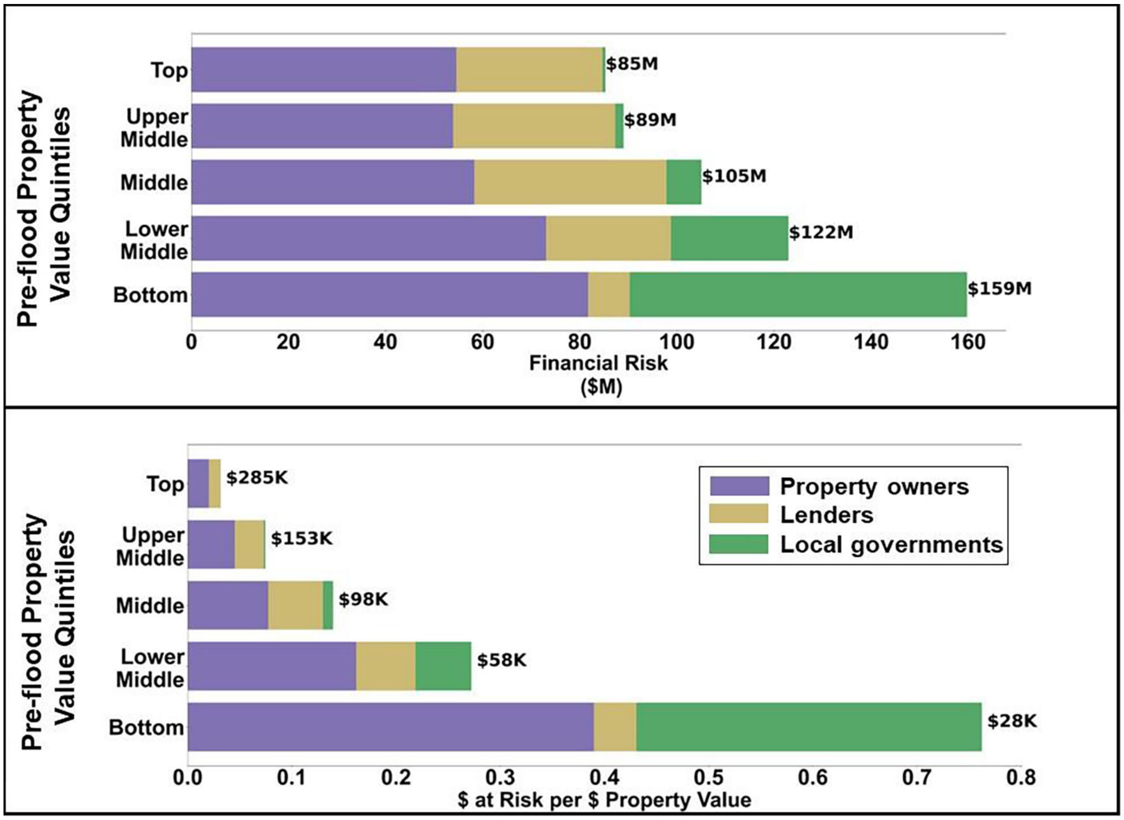

Figure 16.

Financial risk by property value quintile (top) and normalized by preflood property value (bottom). Values to the right of each bar (top) represent aggregate risk generated by quintile for all risk holders and (bottom) the median property value of each quintile.

Table 1.

Descriptive statistics of modelled pre-flood property values across comparative groups

Comparative Group	Median	Mean	95th percentile
Coastal	$113,837	$154,855	$422,553
Non-coastal	$70,337	$100,806	$279,508
Incorporated	$121,767	$169,484	$466,945
Unincorporated	$89,167	$122,681	$323,330
SFHA	$117,938	$160,385	$439,902
Non-SFHA	$81,403	$113,516	$297,075