Financial Risk of Flood Events in Eastern North Carolina

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Executive Summary

North Carolina has been impacted by three "billion-dollar" flooding events since 2015, imposing financial burdens on many communities, particularly in the eastern part of the state. As a result, developing new strategies for mitigating and managing these financial losses has become more urgent, especially as climate projections suggest that flood events will become even more common in the future. Traditionally, estimates of the flood-related risk, as measured by losses, are quantified as either insured or uninsured, information that is useful, but often too general to develop targeted actions as it provides little information as to whom these losses accrue. This research takes advantage of several unique, highly resolved datasets (e.g., parcel level information on flood insurance policies/claims, property values, outstanding mortgage balance) and a novel analytical method to quantify the fraction of flood-related financial risk distributed across four groups within 17 counties that lie within the Neuse River Basin: the federal government (through the National Flood insurance Program (NFIP)), property owners (in this case residential only), mortgage lenders, and local government (i.e. county and municipal).

Using Hurricane Florence (2018) as a case study, residential property owners are determined to retain the largest fraction (44%) of the financial risk, followed by the federal and then local governments, each of which hold roughly 25% of the risk, with mortgage lenders retaining the remaining 10%. It is important to note, however, that the relative fraction of risk accruing to each group varies considerably from county to county across the basin, information that will be important to targeting mitigation and management actions to increase community resilience.

Recommended resilience strategies include policy options that break the cycle of financial losses for flood-affected properties resulting in displacement, foreclosure, and abandonment. This may include subsidizing federal flood insurance premiums in vulnerable areas to shift risk away from local communities, identifying mortgage defaults risks for local lenders or offering mortgage relief directly to households after floods. Identifying communities that will benefit from these and other strategies is crucial for successful implementation, as the distribution of risk is largely dependent on specific vulnerability and flood hazard. Continued work should inform prioritization of these efforts.

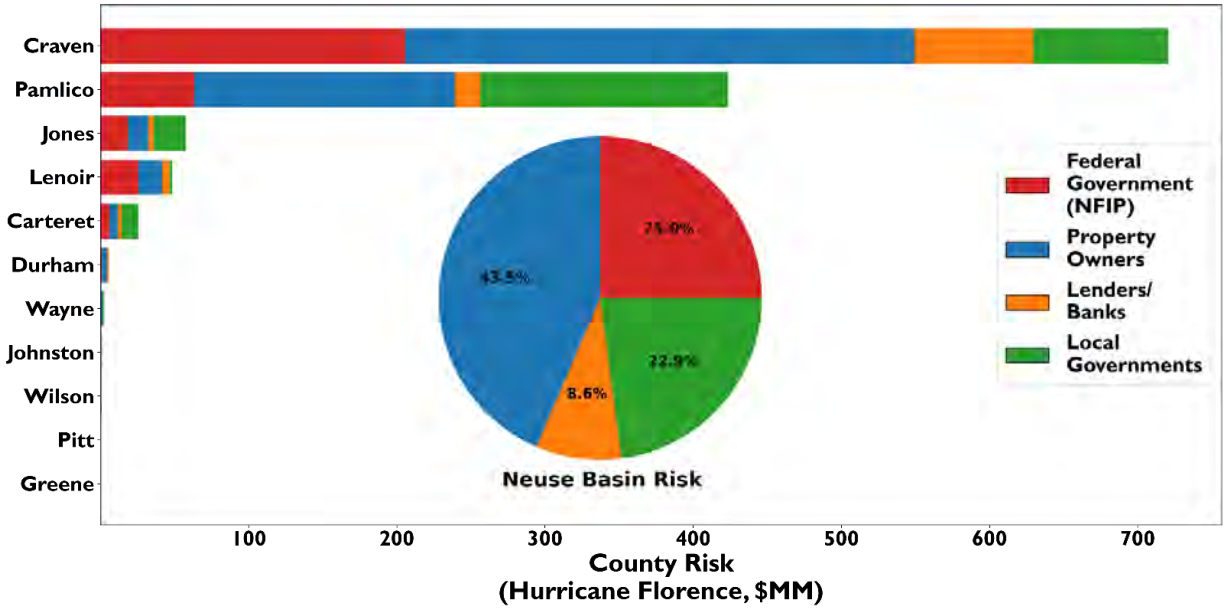

Figure ES- 1: Modeled financial risk (>$20,000) of modeled counties within the Neuse Basin resulting from Hurricane Florence flood impacts on residential properties. Basin-wide risk is inset.

Research questions:

- When property damages due to flooding events occur, how is financial risk distributed between the federal government, local governments, mortgage lenders/banks, and property owners?
- How does this distribution of risk differ by community in North Carolina?
- How can analyses of these risks inform mitigation and management strategies that increase North Carolina's resilience in the face of future flooding events?

Introduction:

Since 1980, flooding and hurricanes have collectively caused over $1 trillion in damages in the United States (NOAA 2020). In North Carolina, three extreme events (Matthew (2016), Florence (2018), and Dorian (2019)) have occurred since 2015 and imposed enormous costs on communities, particularly in eastern parts of the state. Flood insurance provides an initial layer of financial protection for property owners to recover from flood losses, but residential insurance uptake rates are estimated to be only 3.5% in North Carolina compared to the national average of 15% (Marlett, Medders, and Lattimore 2020). Over 70% of the $24 billion in damages resulting from Hurricane Florence are estimated to be uninsured, a level consistent with similar storms, such as Hurricane Harvey (2017), that have made landfall in the United States in recent years (Guyton 2017; Howard 2019). Flood losses are expected to increase in North Carolina as a result of continued development, population growth, and projected increases in severe weather events due to anthropogenic climate change (Carter et al. 2018; Demographer 2021; Tippett 2020). Consequently, quantifying the financial risk of these events by characterizing the cost and distribution of flood losses is an important tool for increasing resilience to future flood events.

While attempts have been made to quantify flood losses at the regional or community scale, it is often less clear to whom the financial risk of these losses accrue, as well as how these risks could cascade through a community (Freni, La Loggia, and Notaro 2010; Wing et al. 2020). Flood damages to residential properties expose property owners to significant financial risks arising from the direct costs

of repairing damages and home equity losses resulting from reductions in property values (McAlpine and Porter 2018). It is often these property owners, and residential homeowners in particular, that are assumed to carry most of the risk of flood-related losses, but the actual distribution of losses across different groups within a community is more complex and largely unexplored. Individual property owners can, and do, pass some of the risk of flood recovery costs along to the federal government by purchasing coverage through the National Flood Insurance Program (NFIP). Nonetheless, most property owners do not buy flood insurance, even when their mortgage terms require coverage (Michel-Kerjan, Lemoyne de Forges, and Kunreuther 2012), and those that do can only recover losses up to the NFIP cap of $250,000 for structural damage (and another $100,000 for losses related to the contents of the home), which maybe insufficient to cover damages.

Many uninsured or underinsured property owners seek to recover from flood events by borrowing funds against the equity they hold in their home, taking advantage of the relatively low interest rates, in order to repair and rebuild properties. If damages are substantial enough such that they exceed the amount of a property owners' equity, there is a tendency for property owners to walk away from their properties (Colman 2020). For properties with a mortgage, this can lead to default and foreclosure, such that the financial burden of the home is then transferred to the lender, who in many cases will attempt to sell the home to an organization willing to repair and then "flip" (i.e. resell) the property (Keenan and Bradt 2020). For example, mortgage payments for damaged properties in Texas after Hurricane Harvey were more likely than non-damaged properties to be delinquent at least 90 days after the storm, with the fraction of those properties that were uninsured being even more likely to be delinquent, need loan modifications, or default compared to their insured counterparts (Kousky, Palim, and Pan 2020). The risk of default is further elevated after a flood because flooded properties often see a reduction in property value (Bin and Polasky 2004; Kousky 2010). If repair costs exceed the post-event market value of a home, lenders may be forced to take losses on any outstanding mortgage balance, as

they are unlikely to undertake any lengthy and expensive foreclosure proceedings intended to recover value from the home (Clowers 2010). This can result in the property being abandoned, at which point responsibility for its maintenance or demolition, as well as the associated costs, are transferred to local government at the municipal or county level (Clowers 2010). In addition, the combined effects of home abandonment, community outmigration, and neighborhood blight can reduce a local government's property tax base, exposing the entire community (flooded and non-flooded alike) to even greater levels of financial risk (Nofal and van de Lindt 2020) as local governments are simultaneously trying to pay to repair damages to public buildings and infrastructure.

Thus, while property owners certainly retain a significant portion of the flood-related loss that impacts their property, these losses have cascading effects throughout a community. As a result, determining the best path by which to make an entire community financially resilient in the face of extreme events is critically dependent on understanding what fraction of flood risk is held by different groups, primarily the federal government, property owners, lenders (local or national), and local government. Quantifying the distribution of flood-related financial risk among these groups, and how this distribution changes across different at-risk regions of North Carolina, will aid in the development of targeted mitigation and relief strategies designed to promote greater resilience in the wake of future flood events.

This work represents an advance through its rigorous parcel-level (i.e., individual property level) estimation of the fraction of flood-related risk that accrues to these four groups, with the focus limited to residential properties in this investigation (consideration of commercial properties will come later). Environmental, financial, and built-environment data are used to model specific flood events and their impact on residential parcels in terms of both damages and declining property values. Flood hazard areas are described via hydrologic variables; the financial data includes residential property sales values, outstanding mortgage balances, and parcel level data on both insurance coverage and claims; and the

built environment is described using characteristics of the parcel and its building that influence both the flood exposure and the property value. Previous studies have adapted machine learning models for natural hazards, such as prediction of the footprint of historic floods, and the estimation of insured damages at specific parcels (Knighton et al. 2020; Mobley et al. 2019, 2020). In this analysis, uninsured damages are also estimated over a broad spatial scale using sparse data on observed insured damages via a machine learning algorithm based on random forests. Property value changes are estimated over space and time using built environment variables and property sales data to interpolate property values for all parcels (Boyle and Kiel 2020; Pace, Barry, and Sirmans 1998; Smith and Huang 1995). Combining estimates of flooding losses (i.e. uninsured damages and property value changes) with census tract level mortgage data (FFIEC 2020) allows estimation of a damage-adjusted "loan-to-value" ratio (LTV) and home equity at each parcel. The relationships between the outstanding mortgage balances, the built equity, property values and damages provide a basis for characterizing parcel-level financial risk which can then be aggregated to the county and regional scale.

Methods:

This analysis benefits from access to several unique and highly resolved datasets that describe the environmental, financial, and built environment systems. This includes parcel level information on flood insurance policies, flood insurance claims and property sales, as well as mortgage information at the census tract level. Built environment variables are used to estimate both uninsured flood damages and property values, and so include both flood-relevant and sales-relevant variables such as first-floor elevation and square footage, respectively. Environmental data are used to estimate total expected damage at the parcel scale, and include soil characteristics, height above nearest drainage site, and other elements that affect local flood wave routing.

A schematic of the modeling framework is laid out in Figure 1, below. The described variables are fed into three models focused on estimation of property values, estimation of uninsured damages, and estimation of outstanding mortgage balance. Methods and results are organized around these three distinct modeling efforts. The outputs from these models are then combined to estimate financial risk at the county and basin-scales. This combination is described by the "LTV analysis" in Figure 1, where a pre-storm equity amount and post-storm adjusted "loan-to-value" ratio (LTV) are calculated and then used to assign fraction of risk to potential risk-holders. Insured damages are retained by the NFIP. Property owners are unlikely to borrow additional funds to repair a home with an LTV greater than 1 (i.e. the outstanding loan on the home is greater than the home's value), and lenders are unlikely to pay for repairs where flooding damages exceed the total value of the property, which can lead to abandonment (Clowers 2010; Gallagher and Hartley 2017). Local governments then assume the risk of properties abandoned by lenders through the costs of maintenance or demolition. This decision-making paradigm will be discussed in further detail later in this section.

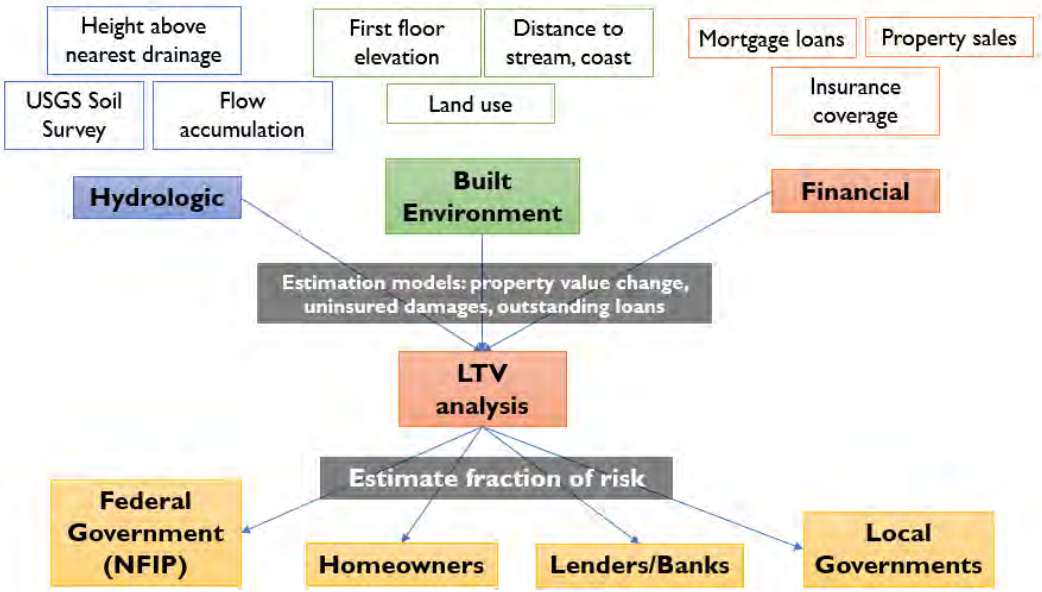

Figure 1: Process for estimation of systemic financial risk from flood events. Environmental/hydrologic components are in blue, built environment in green, and financial in orange. Parties holding financial risk in yellow.

The modeling approach considers distinct but overlapping units of analysis. Variables used in the models are either available at the parcel scale or are assigned to the parcel scale (i.e., characteristics of a building within a specific parcel are tied to that parcel). The individual property parcel will be the primary unit of analysis for this work and will be inclusive of buildings contained within the parcel and with damages that occur directly to buildings tied to the corresponding parcel. However, other terms will be used when appropriate to promote clarity in interpretation. “Property” will be used when discussing property value changes that include the value of the parcel and the building together; this will avoid incorrectly labeling these amounts as “parcel values”, which implies a unique value exclusive of the building value. In discussion of mortgage balances, “property” is sufficiently synonymous with “home” for these purposes to justify its use, and “property owner” will substitute for “homeowner.” However, the included parcels (and properties) include single-family residences only, so many parcels should contain a single building used as a “home” as opposed to a commercial property.

Analysis was primarily conducted for select counties in the Neuse River basin (Figure 2) impacted by Hurricane Florence, chosen as an initial case due to widespread flooding and the magnitude of damages. The Neuse basin was selected as it contains counties such as Craven (home to the city of New Bern) that were highly impacted by Hurricane Florence; as of March 2021, New Bern alone has received over $40 million to address infrastructure and other damages (FEMA 2020). Importantly, multiple counties within the Neuse basin qualified for Individual Assistance from FEMA (direct funds for affected individuals and households, such as to support property repairs) following Florence, indicating losses extended far beyond those covered by insurance.

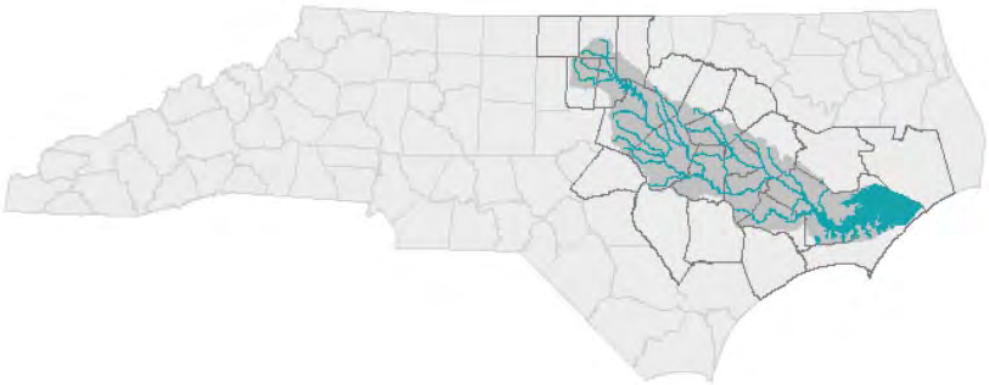

Figure 2: A county map of North Carolina with the Neuse watershed shown in darker grey and major rivers and streams in teal. Image credit: NC DEQ Water Resource Plans, 2010.

Estimating Property Values

A hedonic model is developed to predict residential parcel-level property values by property characteristics and property sales data, following the methods used in previous work that catalogued declining property values in the aftermath of flood events (Bin 2004; Kousky 2010). Property sales data from the First Street Foundation and parcel characteristics from NC OneMap are used. Parcels are filtered for single-family residential by use code before extracting relevant building attributes, including the year built, building square footage, land parcel square footage, distance to county population center (represented by the county courthouse location), and status as incorporated or unincorporated. Residential parcels were extracted for compatibility with the datasets used for the hedonic and other models (i.e., property sales, insurance, and mortgage information), all of which included residential parcels only. Once property values are predicted, results are compared to observed property values from market sales data, yielding "hedonic residuals" that capture the difference between the market value of residential properties and the expected value predicted by the physical characteristics of the

property. Unlike tax assessment data, which can exhibit long delays between re-appraisals, market sales data quickly respond to changing conditions in space and time, allowing for a near-term analysis of the impact of discrete flooding events on property values.

The hedonic residuals were interpolated quarterly (i.e., every three months) for each parcel from 2017 to 2020 via "krigging" to account for correlation in spatially and temporally proximate hedonic residuals. "Krigging" is a geospatial method that predicts values at unobserved locations by relating the variation and distance between observed locations and projecting estimated values to unobserved locations via these relationships. This method utilizes Tobler's first law of geography ("near things are more related than distant things") in both time and space (Le and Zidek 2006; Waller and Gotway 2004). Neighborhood characteristics that would raise or lower property values (e.g., a property sale within the same neighborhood will inflate or deflate a nearby sale) or changes over time (e.g., sales close in time will have more of an effect) are captured and distributed by this process to allot each residential property an appropriate hedonic residual. The interpolated residuals are then converted back into dollar values via the hedonic regression, yielding estimates of property values throughout the Neuse watershed counties from 2017 to 2020.

Estimating Uninsured Damages

Flood insurance uptake in the Neuse basin is below the national average (15%) at the time of Hurricane Florence (Insurance Information Institute 2020). Insurance uptake by county at the time of the event is approximated by comparing active residential policies to all residential parcels (Table 1). Residential parcels are filtered for by parcel use codes provided in the NC OneMap Buildings database and flood insurance policy data is limited to include only active policies at the time of the event (in this work, defined as September 10, 2018 to September 30, 2018). Most counties in the Neuse basin have

less than 1% of residential parcels insured, with the maximum rate of flood insurance uptake observed in Carteret County at 5.02% (Table 1). The 17 counties listed below are the focus of this analysis.

Table 1: Hurricane Florence Residential Insurance Coverage in Neuse basin counties*

County Name	% Residential Parcels Insured, Hurricane Florence
Carteret	5.02%
Craven	2.49%
Durham	0.53%
Franklin	0.10%
Granville	0.05%
Greene	0.28%
Johnston	0.36%
Jones	0.78%
Lenoir	0.77%
Nash	0.37%
Orange	0.36%
Pamlico	4.21%
Person	0.02%
Pitt	0.79%
Wake	0.33%
Wayne	0.40%
Wilson	0.00%

* Beaufort, Duplin, Edgecombe, Harnett, Onslow, and Sampson counties are excluded from this model, as they have negligible land area within the Neuse basin.

Machine learning random forest models are algorithms that examine combinations of independent variables via detailed decision trees to predict the value or classification of dependent variables. The data are split into two groups, one where the dependent variable is known and one where prediction is needed. The set with known dependent variables is randomly split again into testing and training sets. The model learns which combinations of independent variables are likely to yield known values of the dependent variable within a training dataset, then validates its performance by practicing on the "testing" dataset and comparing its predictions to the known values. The model can then apply that learning to data with the same inputs to predict values or classifications for the unknown,

dependent variable. Random forest algorithms have been successfully used to generate flood hazard maps in Texas (Mobley et al. 2020), and to predict flood insurance claims at a census tract level in New York (Knighton et al. 2020). Other studies have used random forest to estimate the extent of flooding from particular rainfall events (Kim and Kim 2020) or the potential for flash floods based on environmental variables (Band et al. 2020). This work takes a somewhat new approach by using these methods to predict uninsured flood damages, given the locations of flood insurance policies-in-force and claims after a single flood event (Hurricane Florence).

Parcel-level NFIP claims and policy data are used to train a random-forest model to predict flood damages from Hurricane Florence. The testing and training datasets include parcels with either flood policies or claims, as information about damages can be inferred from these variables. Parcels with a flood insurance policy, but no claim, are treated as pseudo-null values and assumed to have no flood damage. Parcels with an insurance claim are assumed to have experienced flood damage. The trained random forest model is then used to predict presence of flooding and the magnitude of damages resulting from flooding at uninsured parcels (i.e., no policy or claim data). The Hurricane Florence specific model includes insurance policies in force and claims made for damages occurring over the period of September 10, 2018 to September 30, 2018, as Florence made landfall in North Carolina on September 14, 2018, and over 95% claims were filed by the end of September.

Independent variables used to build the random forest model (Table 2) describe the flood hazard (likelihood of a given location to flood during Hurricane Florence), the characteristics of the affected property, and the presence or absence of flooding as described by flood insurance data. The independent variables were extracted from the listed datasets only for the portion of each county located within the Neuse basin.

Table 2: Machine learning model input variables

Variable Type	Variable Name	Source	Geographic Resolution	Description
Financial	Insurance Claims (Building Damages only)	**FEMA (NFIP)[i]	Parcel	Paid claims towards building damages
Financial	Insurance Policies in force	**FEMA (NFIP	Parcel	Policies covering the event period (9/10/2018 – 9/30/2018)
Built environment	First floor elevation	NC OneMap[ii]	Parcel	Elevation of first floor above sea-level
Built environment	FEMA-designated flood zone	NC OneMap	Parcel	Detailed flood zone designation for parcel
Built environment	Foundation type	NC OneMap	Parcel	Building foundation (fill, slab, etc.)
Built environment	Building type	NC OneMap	Parcel	Primary building material (stone, wood, etc.)
Built environment	Building value	NC OneMap	Parcel	Tax-assessed value
Built environment	Surrounding impervious surfaces	National Land Cover Database, 2016[iii]	30mx30m raster	Percent impervious surface with four circular areas of increasing radii, centered around parcel
Built environment	Distance to nearest stream	National Hydrography Dataset[iv]	Parcel	Distance from parcel centroid to nearest stream (order > 2)
Built environment	Distance to coast	National Hydrography Dataset	Parcel	Distance from parcel centroid to coast
Environment/ Hydrologic	Flow accumulation grid	National Hydrography Dataset	10m x 10m raster	Area upstream flowing into each raster cell, averaged over the parcel area
Environment/ Hydrologic	Height above nearest drainage (HAND)	Oak Ridge National Laboratory[v]	10m x 10m raster	Height over each raster cell above the nearest drainage feature, averaged over the parcel area
Environment/ Hydrologic	Hydraulic soil conductivity (Ksat)	USGS SSURGO[vi]	--	Centimeters/hour infiltration by soil type

**This study used an unredacted version of the cited dataset, obtained directly from FEMA.

All variables were tied to individual parcels, then aggregated to the county and the basin scale (i.e., the 17-counties defined here as the Neuse basin). The parcel-level dataset is run through both a classification model, to determine flood hazard, and a regression model, to estimate the magnitude of uninsured damages in dollars. Each model utilizes 2000 decision trees, and a 75%/25% split between training and testing datasets. The classification model is trained and tested on 3,899 individual insurance claims and 4,581 policies, where addresses with claims were classified as 'flooded' and addresses with policies, but no claims, were classified as 'not flooded'. Of these data, 682 were defined as "not flooded" initially, as they had a policy but no claim. The training and testing sets are slightly smaller (<15%) for the regression model, as this model is only trained on parcels that were defined as flooded and damaged through filing of a flood insurance claim. The trained classification model is used to estimate the likelihood of flooding in parcels with no insurance information (policies or claims), and the regression model predicts a damage amount for parcels classified as flooded.

The likelihood threshold used to classify parcels as flooded or not flooded represents a tradeoff between capturing true positives and excluding false positives. While methods exist that aim to best balance this tradeoff (He and Ma 2013), applied to this RF model they result in damage estimates that contain a smaller portion of uninsured damages than overall damage estimates made by industry leaders such as RMS and CoreLogic. Here, a classification threshold (0.69) is selected that results in uninsured damages comprising 70% of the overall damages across the study region, bringing model output in line with earlier estimates for Hurricane Florence in the Carolinas (CoreLogic 2018; RMS 2018).

The performance of the random forest (RF) classification model can be described by an "area under the curve" (AUC) approach that describes the area underneath a "receiver operating characteristic" (ROC) curve relating true positives predicted by the model to false positives predicted by the model, with positives indicating the presence of flooding. An algorithm with no predictive power would exhibit an AUC equal to 0.5 whereas a model with high predictive power would exhibit an AUC

closer to 1. The regional Neuse model has an AUC of 0.91, which is consistent with accepted performance of these models in the (Knighton et al. 2020; Mobley et al. 2020). The ROC curve for this model is included in the Appendix. The most influential independent variables in determining the presence of flooding by the classification model are distance to the coast and first floor elevation; variable importance for all variables can be found in the Appendix. The RF regression model's performance is evaluated in a similar way, with the degree of correlation (R^2) between predicted and observed values of flood damages providing the performance. The RF model has an R^2 of 0.36. Prior studies have discussed the difficulty of predicting damages from observed data, for example due to a lack of consistency between damage appraisals and derived depth-damage relationships (Freni, La Loggia, and Notaro 2010; Wing et al. 2020). This can often result in damage estimates that can be highly uncertain at parcel scales (Merz et al. 2004).

Confidence in the performance of the RF model is supported by comparisons of the estimated damages to those modeled via a more time and resource intensive method by the state of North Carolina for the same event (Figure 3). After major flood events, the state of North Carolina follows a standard method of damage estimation using a combination of hydrodynamic models and depth-damage curves. This analysis uses the statistical and analytical models described here. The damages estimated in this analysis include modeled uninsured damages and known insured damage, which do not distinguish between sources of flood waters; the state modeled estimates include riverine and coastal flood damages for residential parcels (both insured and uninsured) in the Neuse basin counties (North Carolina Department of Public Safety 2018). For most modeled counties, the project estimates closely reflect the state modeled estimates, as seen by the proximity of labeled counties to the 1:1 line shown in red. This demonstrates the potential utility of the RF method in estimating post-flood damages quickly and at low cost.

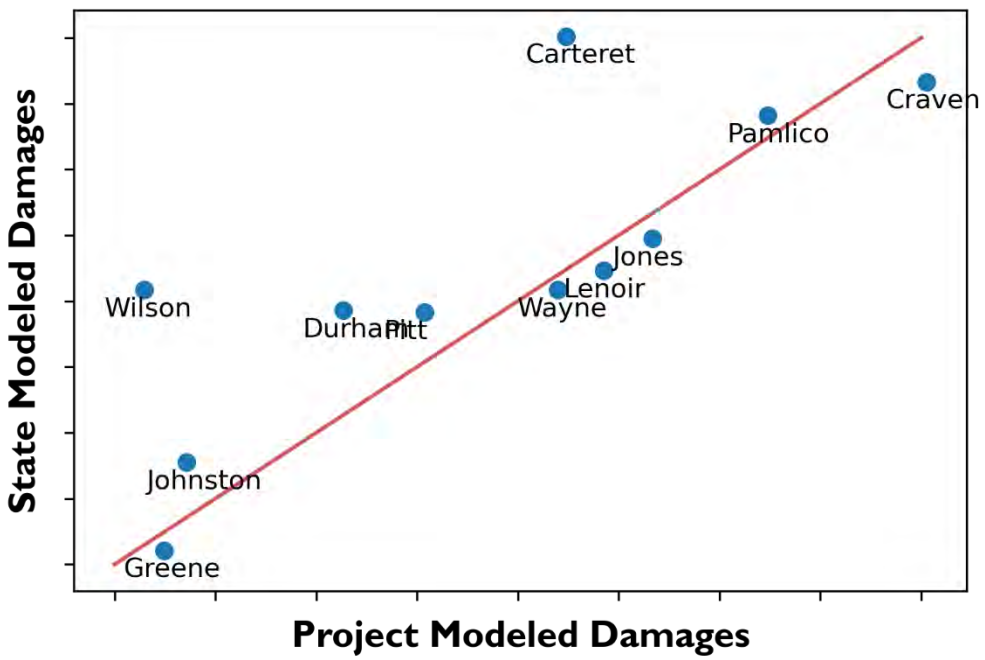

Figure 3: Comparison of Hurricane Florence modeled damages by the state of North Carolina (y-axis) and by the random forest regression model (x-axis). The 1:1 red line is included for reference, and is not a fitted trendline, but rather a way of visualizing the similarities in results across the two methods.

Estimating Outstanding Mortgage Balance

Outstanding property mortgage loan amounts and existing loan-to-value ratios identifiable by census tract are available for the year 2019. These data are publicly available from the Federal Financial Institution's Examination Council (FFIEC) and include mortgage loans issued in the year 2019. As mortgage information is not available for all parcels in the census tract, the existing loan data is treated as a historic dataset that can be resampled to create synthetic mortgages that are characteristic for any specific tract. Mortgages from the FFIEC dataset were assigned to parcels randomly within census tracts to simulate property sales that would reset the terms of the loan. Mortgage balances are simulated over a thirty-year period assuming a constant annual repayment schedule, with new mortgages randomly assigned to parcels in every year. This random assignment does not assume that each parcel begins a new mortgage each year, but rather allows for repayment of different lengths to simulate the different

mortgage maturities and timescales of property ownership. At the end of the simulation, the remaining mortgage balance at each parcel yields a tract-specific distribution of LTV ratios at the time of the flood.

Estimating Financial Risk

In this analysis, the federal government is determined to hold the financial risk of flood events through the NFIP and the payouts this program makes of flood insurance claims to insured properties. Property owners are assumed to hold the risk if the reduction in property value after the storm, uninsured damages, or the sum of the two are less than the equity the property owner maintains in the property. Once the sum of property value reduction and uninsured damages exceeds the equity, the property owner is assumed to forfeit that equity, default on the mortgage, and walk away from the property. For properties holding a mortgage, this results in the property becoming the responsibility of the mortgage lender. For properties in a similar situation without a mortgage, financial responsibility for the property reverts to the local government, which may either demolish, maintain, or repurpose it.

At the time of the flooding event ,the simulated loan-to-value ratio and the interpolated property value to provide an estimate of owner equity. As the mortgage balance remaining to pay is fixed post-storm, the property owner equity is effectively impacted with property depreciation and uninsured damages. This “decrease” in equity limits the capacity to borrow for repairs, as the low-interest loans offered to property owners by the Small Business Administration (SBA), Federal Housing Administration (FHA), or private lenders are contingent on the value of the mortgage (i.e., equity). Lowered borrowing capacity increases the likelihood of default and eventual abandonment (Figure 4). The conceptual framework used to assign risk in this analysis is shown succinctly in the rightmost column of Figure 4, as increased flood damages relative to property value determines where financial risk is retained among the four parties.

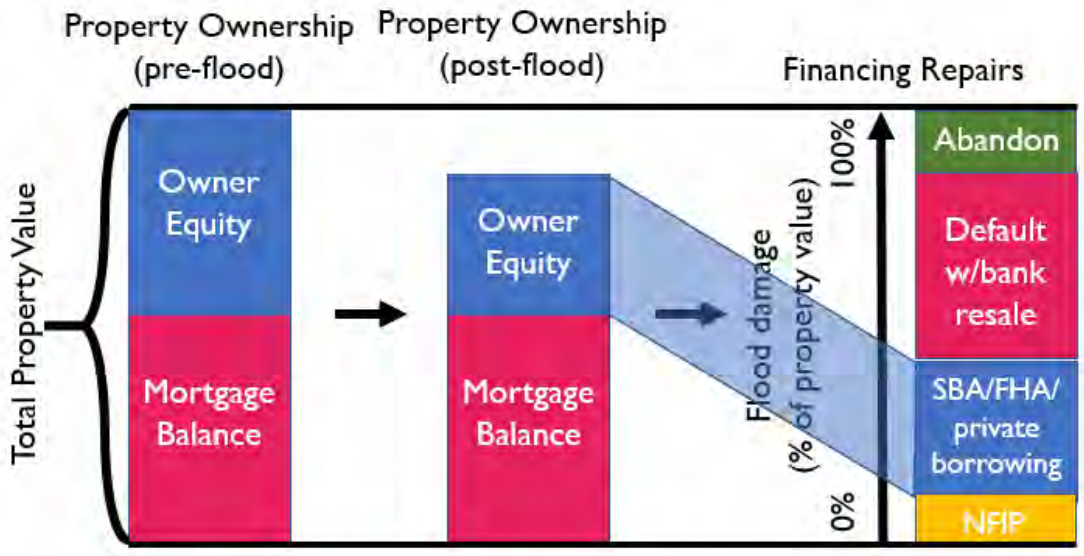

Figure 4: The impact of flood events on property ownership decisions related to repairing or abandoning the property. As mortgage balance remains fixed, decreases in property value reduces owner equity, which in turn affects the availability of low interest borrowing to repair damages. In the right-most bar, risk accrues to the federal government (yellow), the property owner (blue), the mortgage lender (pink), or the local government (green) depending on magnitude of damages.

The maturity of the mortgage is influential in determining which group holds the financial risk for flood-affected parcels. As equity grows over time, the level of flood-related damages necessary to bring about default and abandonment increases, as property owners are more likely and more able to borrow sufficient low interest funding to repair uninsured damages (Figure 5). In this case, property owners retain a greater fraction of the risk of uninsured damages, but have greater capacity to borrow inexpensively, and absorb the potential resale implications of property depreciation, thereby avoiding mortgage default.

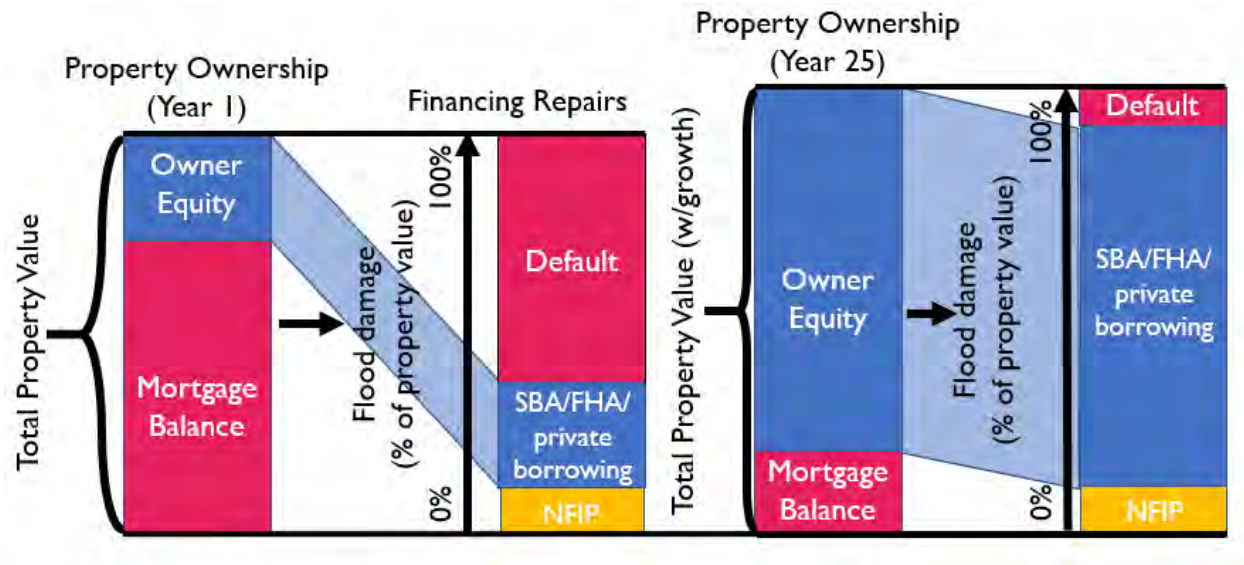

Figure 5: The impact of flood events on ability of property owners to retain financial risk. Property owners borrow against their equity to repair uninsured damages; as the mortgage matures, equity grows, increasing low interest borrowing capacity. Though risk of default is reduced, it is still possible depending on magnitude of damages. Financial risk is retained by the federal government (yellow), the property owner (blue), or the mortgage lender (pink).

The outstanding mortgage is then combined with the estimated uninsured damages at the parcel, (which requires additional debt on the part of the property owner to address) to yield an adjusted loan amount. This adjusted loan (outstanding mortgage loan plus uninsured damages) can be compared to the estimated property values to result in an adjusted, post-flood LTV. An LTV value greater than 1 indicates that a mortgage is at risk of default, and in this analysis is assumed to default, passing the financial risk to the mortgage lender. For the mortgage lender, this financial risk amounts the difference between the outstanding mortgage balance and the level of the property owner's equity, as this portion of the mortgage will not be repaid to the lender after property owner default. The mortgage lender may be able to resell the foreclosed property to recoup some of its losses; however, if storm damages exceed the post-flood property value, as becomes more likely if the post-flood property value also declines, there may be no buyers willing to pay the costs to return the property to a marketable state. In this case, the lender is assumed to abandon the property, losing the remaining

property value, which also leads to it becoming the financial responsibility of the local government to demolish, maintain or repurpose. In this analysis, the financial risk for local governments has been limited to $20,000 per abandoned property (Sumell 2009), though this cost may vary by community. Other costs to the local government, not considered in this analysis, include long-term decreases in the tax base along with social and financial costs of neighborhood blight. While quantifying these costs is beyond the scope of this project, it would add to that portion of the risk assigned to local governments estimated in this work.

To model the central research question of who holds flood-related financial risk, the relationship between the equity, uninsured damages, and changes in property value are determined by a series of decision-making thresholds which are then used to "assign" risk to a particular party (Figure 6). Financial risk is estimated for all parcels classified as damaged by the machine learning model; within this subset of residential parcels, the magnitude of equity, insured and uninsured damages, and property value determines the amount of risk accruing to the federal government, property owners, lenders, and local governments.

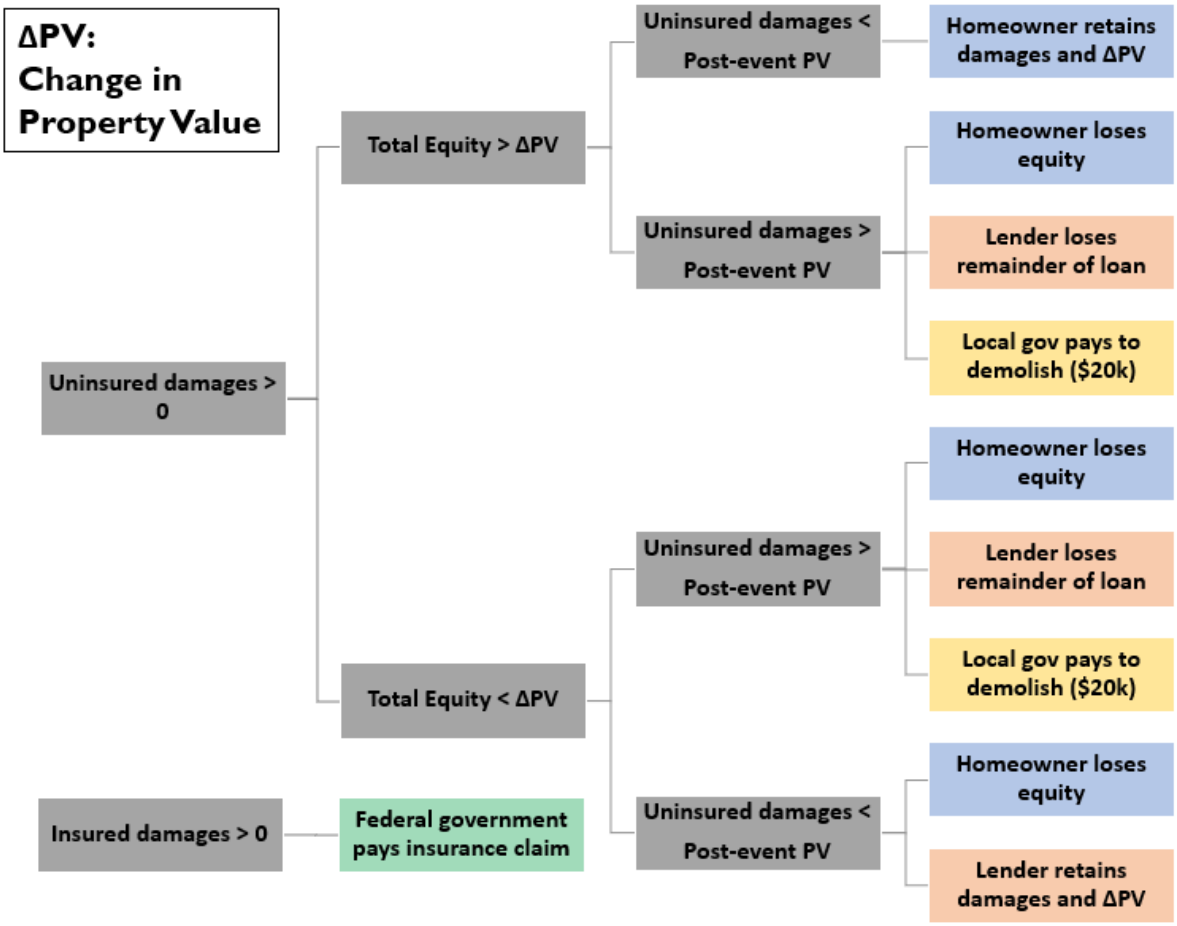

Figure 6: Estimation of financial risk through comparisons of equity, damages, and property values (PV). Comparisons in gray; property owner losses in blue; lender losses in orange; local government losses in yellow; federal government in green.

Findings:

Results detailed below, including model outputs and estimates of financial risk apportionment across the four groups, are specific to Hurricane Florence in the 17 counties of the Neuse Basin. The results indicate the utility of these detailed and location-dependent analyses in making more highly resolved estimates of the financial risk of North Carolina communities to flood events.

Property Values

Property values are estimated at the parcel-level, both before and after Hurricane Florence, using the hedonic model and krigging method discussed above. The difference between these estimates yields a change in property value resulting from the flood event. An example of these changes among residential parcels in New Bern, North Carolina, which experienced high levels of flood damages in Hurricane Florence (FEMA 2020), is shown in Figure 7. In the figure, red shades indicate decreases in property value and blue shades indicate increases; white indicates no significant estimated change. Sharp boundaries between neighborhoods with increased and decreased property values illustrate the spatial distribution of property sales in the aftermath of Hurricane Florence; this reflects the market response to the flood event and underscores the advantage of using property sales over tax-assessed values, which would not be expected to respond as swiftly.

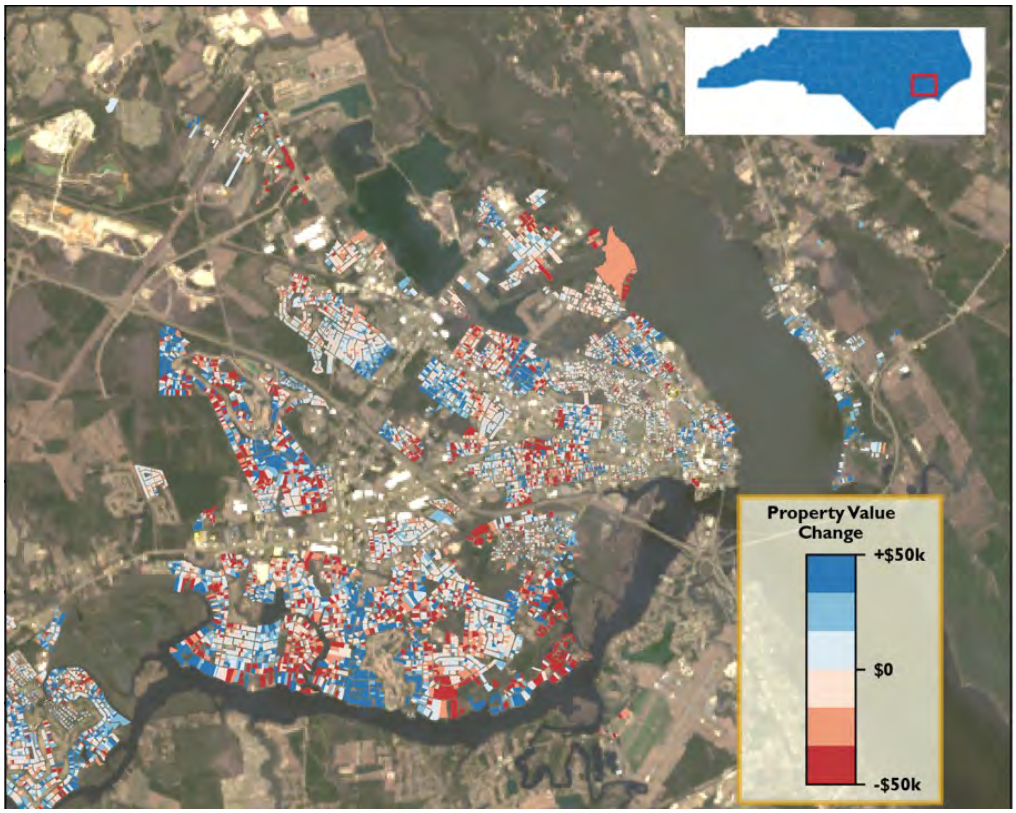

Figure 7: Changes in property values after Hurricane Florence in downtown New Bern, NC.

Uninsured Damages

Parcel-level estimates of uninsured damages are aggregated by census tract to illustrate the distribution of damages throughout the Neuse watershed (Figure 8). Insured damages at the census tract level are included for comparison. The most uninsured damage occurs in census tracts within the southernmost region of the Neuse basin, with a maximum of roughly $46 million in a tract within Craven County. The average damage per census tract across all modeled counties is just over $1 million, but only 22% of Neuse basin tracts are estimated to have incurred any uninsured damages from Hurricane Florence. This pattern is reflected in Figure 8 below, as medium to dark red tracts indicate higher levels of damages, and are concentrated spatially, while the lightest beige indicates little to no damage. A similar pattern is observed in insured damages, which are also aggregated to the census tract level. Census tracts with insured damages have a maximum damage of $49 million, average damage of $1 million, and roughly half (47%) of tracts experienced insured damages.

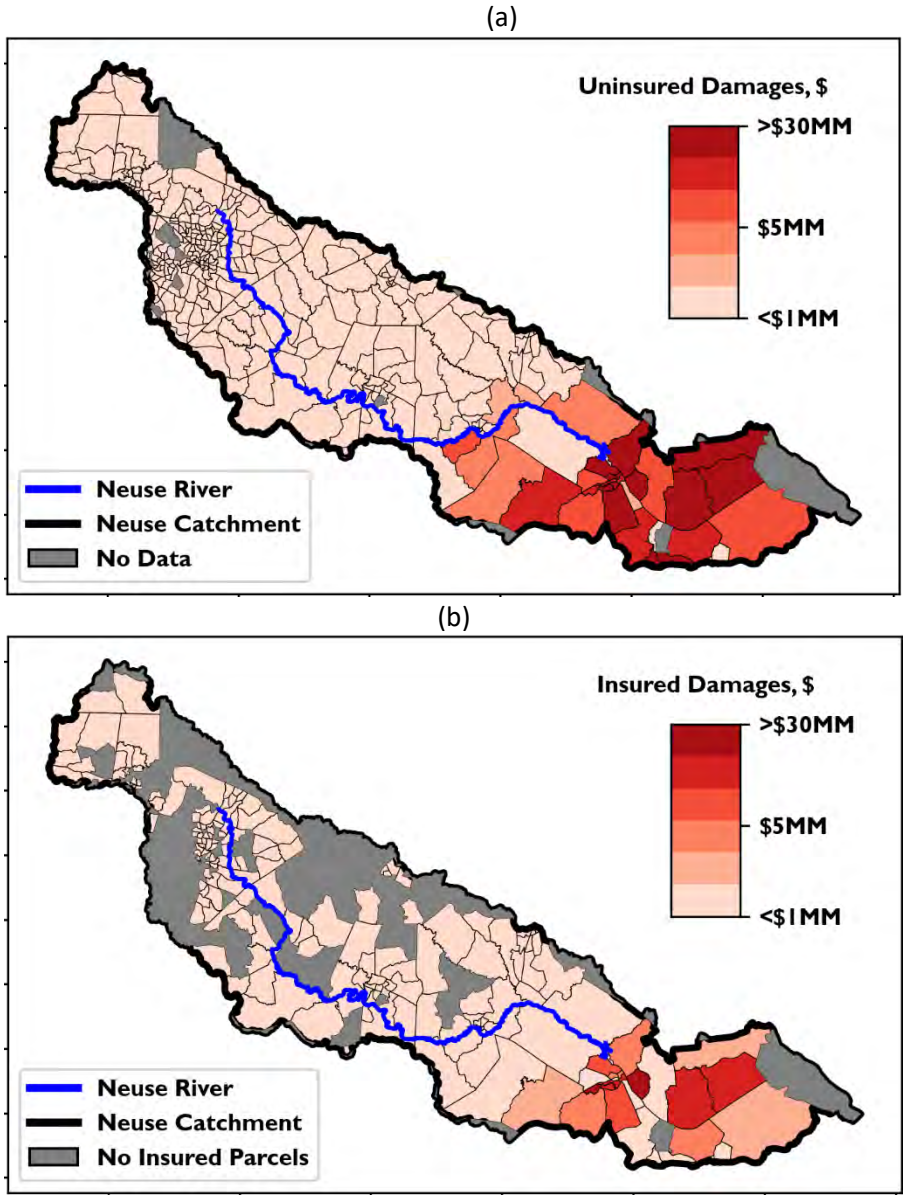

Figure 8: Hurricane Florence residential flooding damages at the census tract level for a) uninsured parcels estimated via the random forest model, and b) insured parcels identified via NFIP data. Gray areas in a) were not modeled due to lack of data, and in b) represent no insured parcels. Light beige areas include tracts with damages as low as $0.

Aggregate damages are averaged over the number of uninsured, residential parcels included in the model within each census tract (Figure 9). Across all parcels, the mean parcel-averaged uninsured damage is $1,200 per residential parcel with a maximum of roughly $35,000 per parcel. For insured parcels, the parcel-averaged insured damage averages $9,000, and the maximum exceeds $130,000.

The highest uninsured damages, both aggregated at census-tract scale and parcel-averaged, are in the southernmost region of the Neuse basin. Aggregate insured damages are also concentrated in this area. Conversely, parcel-averaged insured damages are spread more evenly through the Neuse basin, most likely due to the small number of insured parcels used to generate the parcel-averaged estimate.

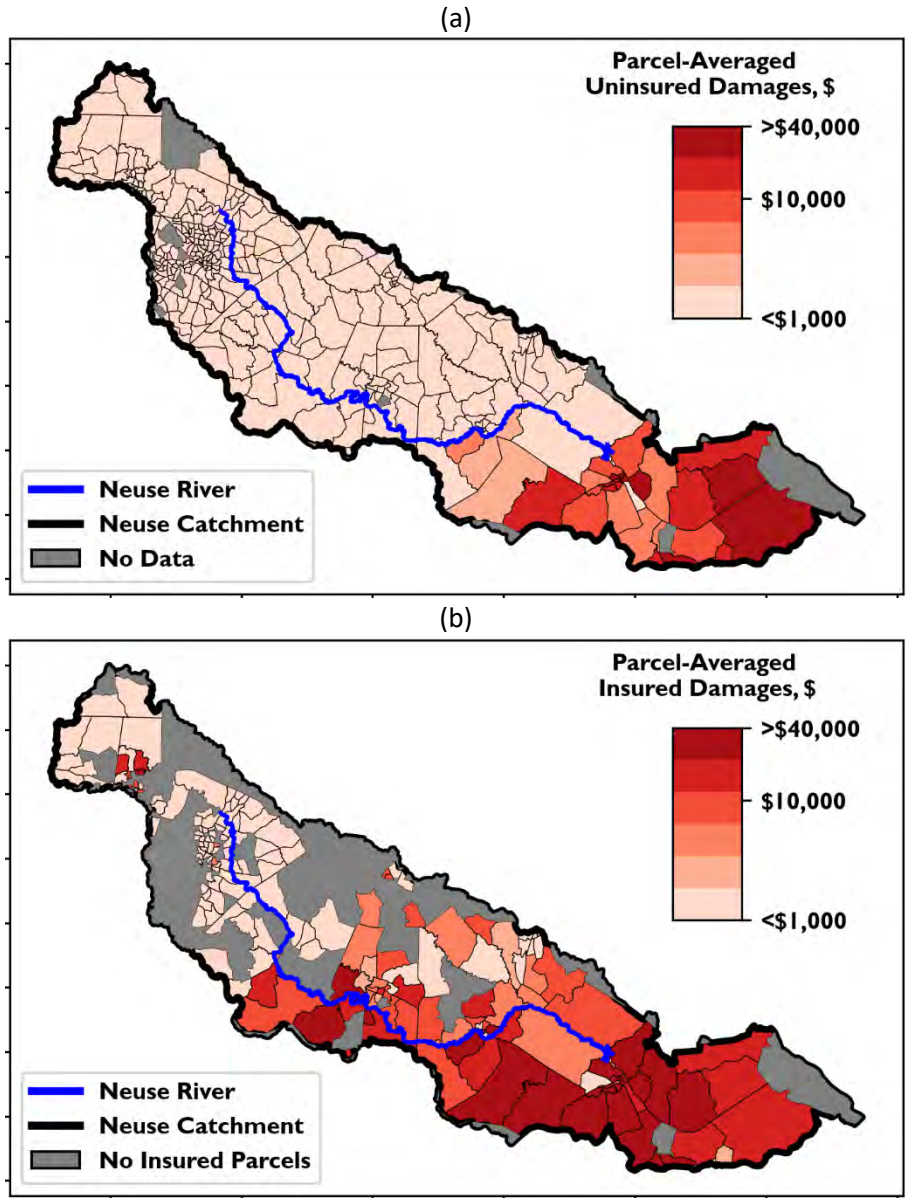

Figure 9: Average damage per residential parcel in each census tract, a) as estimated for uninsured parcels by the random forest model, and b) for known insured damages. Grey indicates lack of data; beige indicates $0 to little damage.

Select counties, such as Orange County in the far upland sections of the Neuse basin, have little or no uninsured damages predicted by the RF model, but were estimated by the state to have experienced substantial damage from Hurricane Florence. While state estimates are challenged by the same uncertainties in damage estimations, this may also present an opportunity for model improvement. The discrepancy between affected census tracts when comparing modeled uninsured damages (22%) and observed insured damages (47%) also presents an area for model improvement. Although insured damages were not large in magnitude across the basin, there may be low magnitude losses that are not currently being predicted accurately by the RF model. Future work aims to continue model improvement, including expanding the methods of validation in addition to the comparison to state modeled estimates shown in Figure 3.

Outstanding Mortgage Balances

Combining uninsured damages with property value changes and existing loan-to-value ratios (LTV) yields post-storm adjusted LTVs that are used to estimate financial risk accruing to the different groups. If the LTV exceeds 1, property owners are assumed to default on their mortgage, as investing time and resources to make repairs will be less financially attractive (refer to Figure 6). Mortgages assumed to default in New Bern, North Carolina after Hurricane Florence are shown in Figure 10.

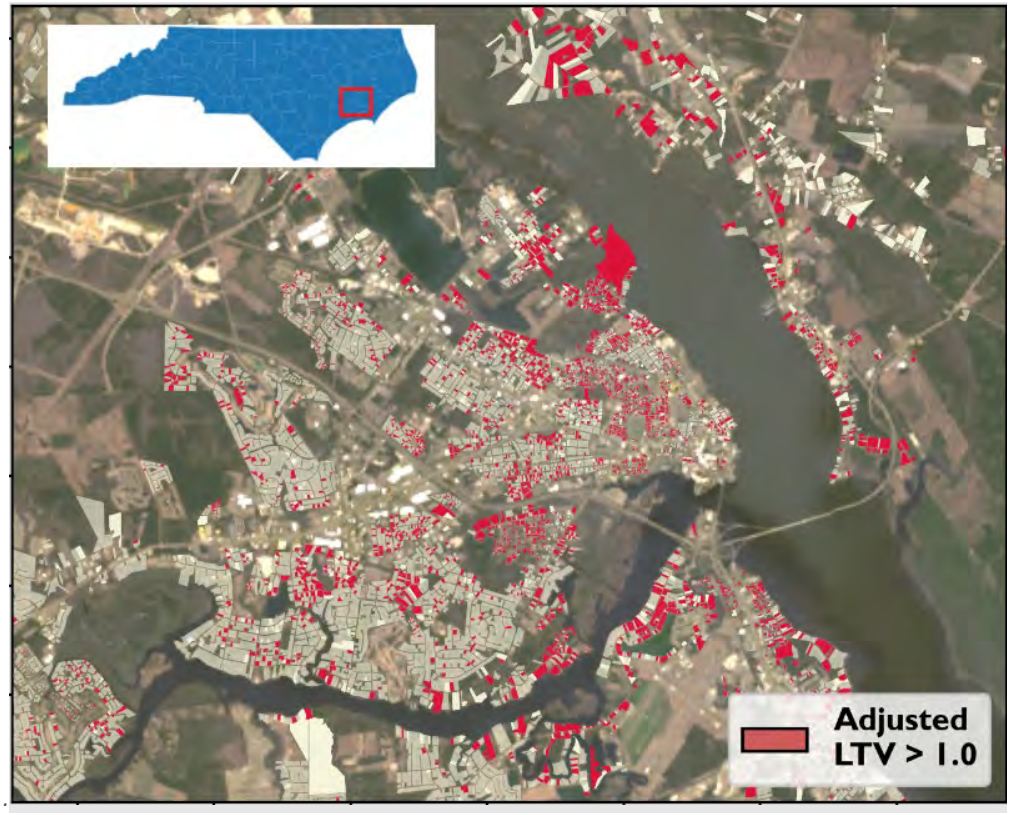

Figure 10: Residential parcels in New Bern, NC with a modeled adjusted LTV >1 shown in red. With the loans exceeding the value of the property, these mortgages are considered at risk of default.

Financial Risk Estimates

Following the decision-making criteria outlined in Figure 6, the fraction of flood loss risk in each county is assigned to the federal government, property owners, mortgage lenders, or local governments (Figure 11). It is important to note, that the distribution of risk varies significantly from county to county across the Neuse basin. Identifying these differences is a critical part of this analysis as it should allow for more targeted risk mitigation and management actions related to future flooding events. The absolute size of the risk in several counties makes distinguishing the amounts and distributions of risk in the less populated counties more difficult to see in this figure, but a table of the distribution of risk for each county can be found in the Appendix.

Some of the 17 counties originally included in the Neuse basin are not listed in the risk profile analysis, as the RF model categorized these counties as "undamaged" with respect to residential parcels located in the Neuse. This includes Franklin, Granville, Nash, Orange, Person, and Wake counties. Therefore, all counties included in Figure 11 are estimated to have suffered nonzero losses, even if these losses are comparatively small relative to the most damaged counties (Craven and Pamlico). The results were only calculated for portions of the county that were included in the Neuse watershed random forest model. For counties that span multiple watersheds, these numbers may be an underestimate of total county-wide financial risk due to flooding from Hurricane Florence.

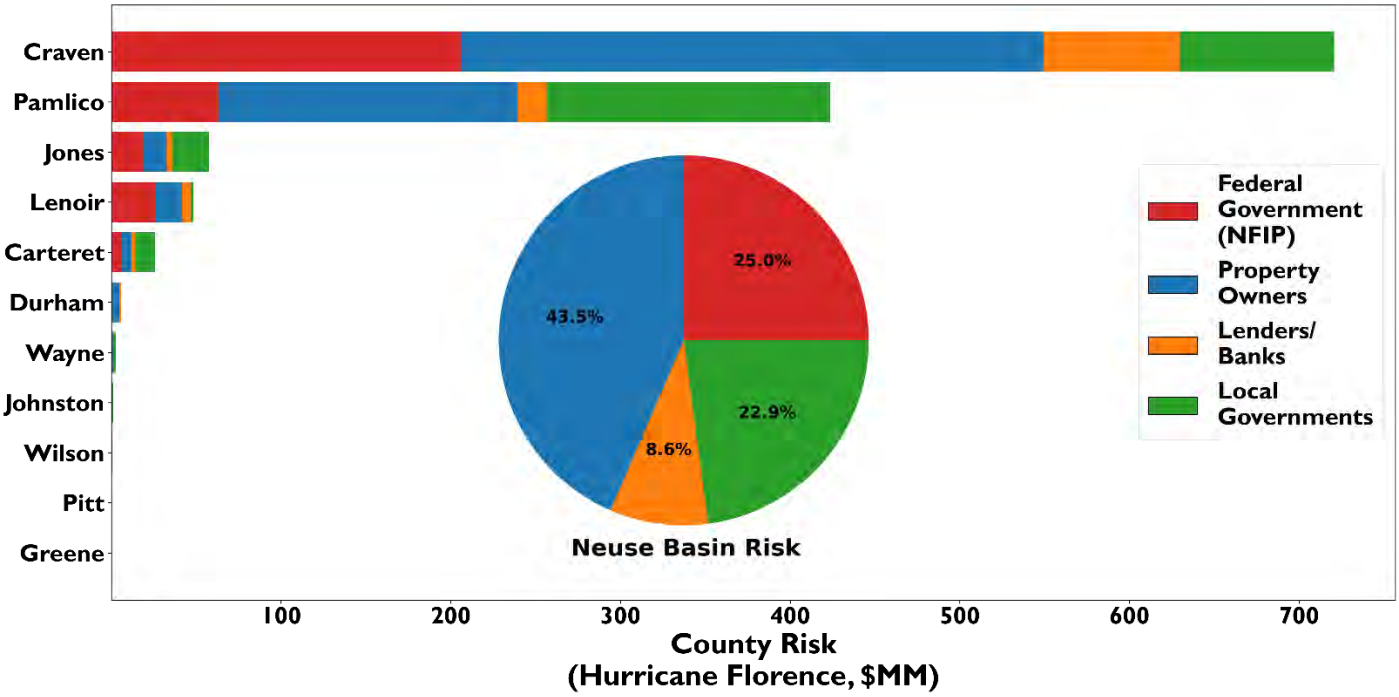

Figure 11: Fraction of risk accruing to groups within Neuse basin counties. All counties in figure have non-zero financial risk from Hurricane Florence flooding. Basin-wide risk is inset.

Though the relation of the insurance coverage, property value, damage, and equity determines the "assigned" fraction of total financial risk accruing to each group, the risk itself is driven by the combination of uninsured damages and any reductions in property value. Addressing these two drivers of risk calls for different types of policy actions, so understanding their contributions is useful for

resilience planning. For example, as reductions in property values in flooded neighborhoods can have a negative impact on both flooded and unflooded properties alike, detailing where post-flood property value decreases are more prevalent could be predictive of neighborhood-wide or community-wide property value losses. These areas could benefit from policies or programs that counteract these effects of the flood.

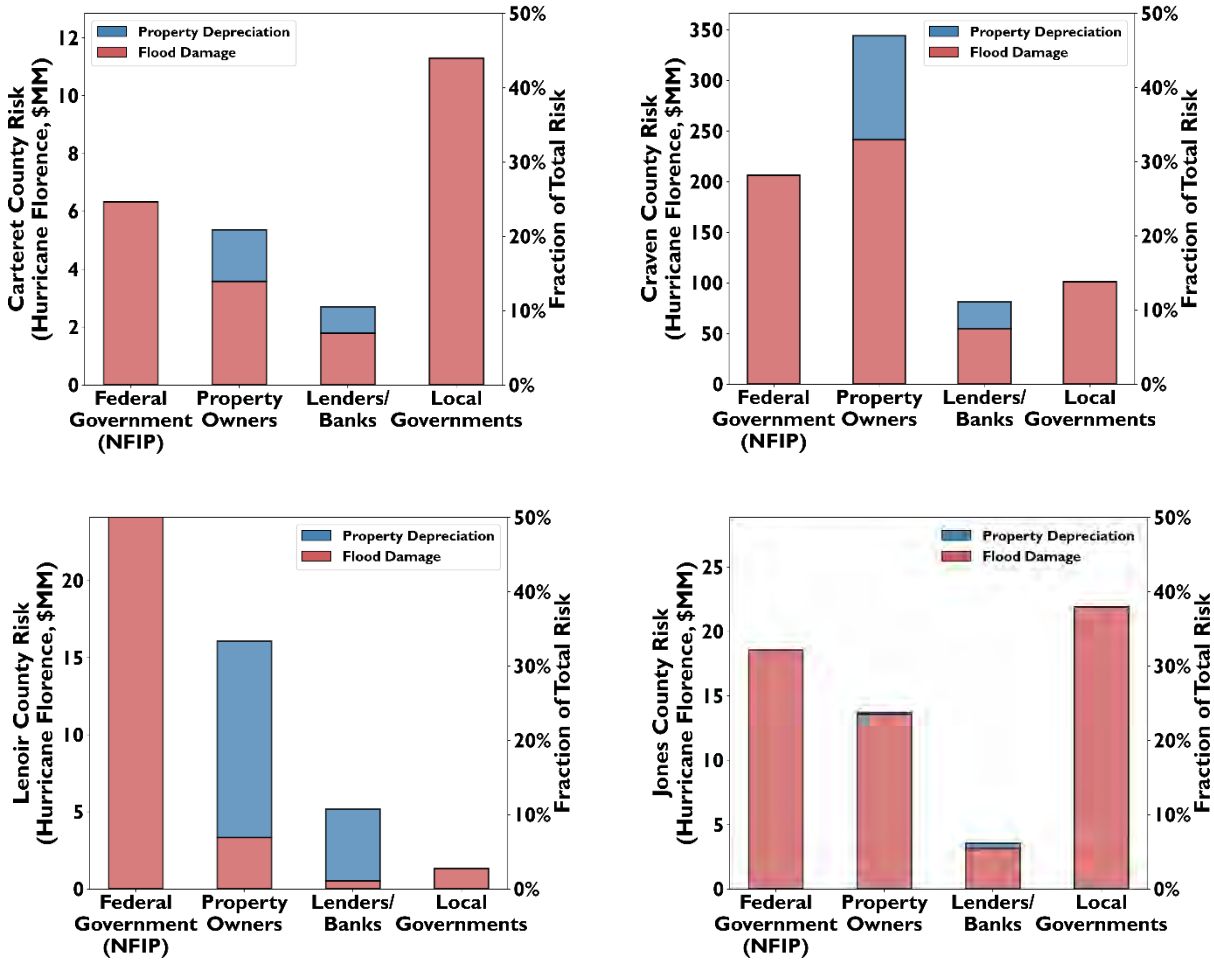

Figure 12: Modeled losses due to property depreciation and flood damages in (clockwise from upper left) Carteret, Craven, Jones, and Lenoir counties. Note the differing left-hand y-axis for each county to accommodate county specific levels of loss, and the consistent righthand y-axis indicating the fraction of risk to each risk holder, per county.

The risk to each party is also summed across the 17 counties in the Neuse basin to yield estimates of basin-wide risk (Figure 13). Property owners carry the largest fraction of the basin-wide

financial risk (44%), while the mortgage lenders retain less than 10%, with the federal government (via the NFIP) and local governments each holding roughly 25% of the risk each.

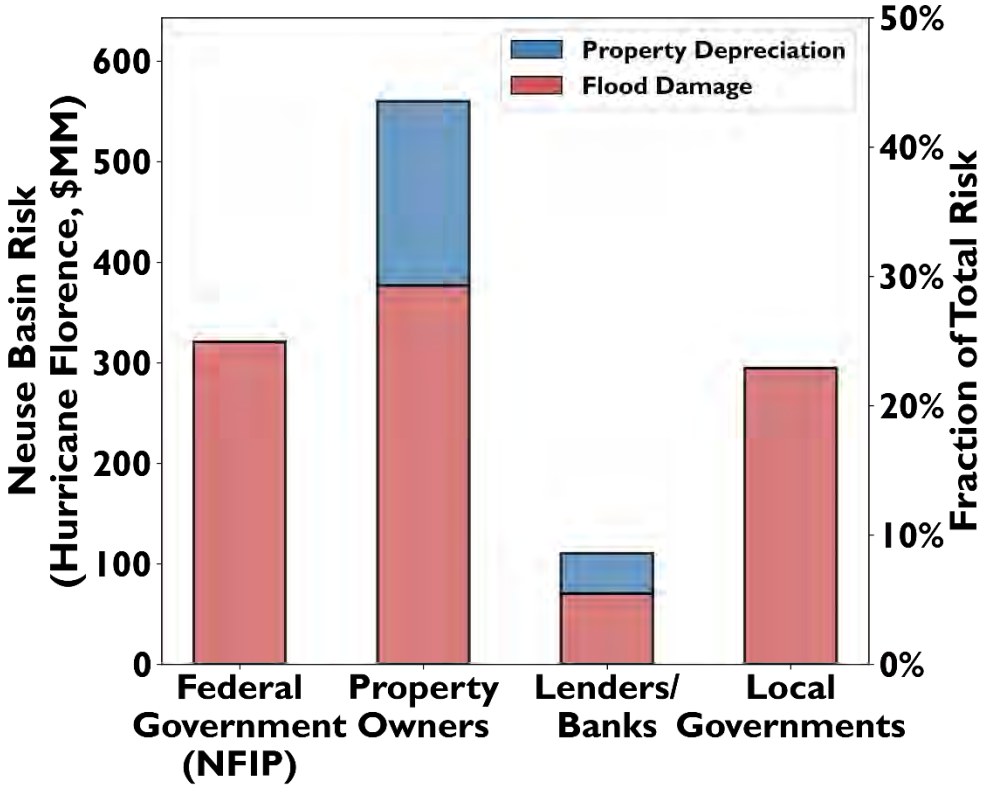

Figure 13: Hurricane Florence losses due to depreciation and damages across the Neuse watershed. Damages are only charted for counties classified as damaged by the random forest model.

These results provide a more detailed analysis of how financial risk from floods cascade through local communities in North Carolina. Though specific to the scenario that was modeled -- historic flooding attributable to Hurricane Florence in the counties of the Neuse Basin—the results indicate that losses accrue to different groups in different proportions from county to county. Property owners bear the most risk at the basin-wide level, however, the risk held by other groups is substantial, in some counties exceeding 50% of the total, and the distribution varies greatly between counties. This analysis identifies such counties where property owners do not hold most of the risk, such as Carteret; these case studies raise questions that deserve continued effort to understand, including what factors

may lead to this difference in risk accruing to the different groups across North Carolina counties. Other counties, such as Lenoir, exhibit the protective nature of high levels of flood insurance uptake, as most damage losses accrue to the federal government through NFIP policies, and not to property owners, mortgage lenders, or the local government. Without additional analysis, these impacts cannot yet be extrapolated to other North Carolina counties for the same event, nor for the same counties experiencing other flood events, historic or in the future. Future work aims to explore additional flood events, expanded geographic areas, and the potential for these models to expand to provide predictive capacity related to future flood losses. These detailed, county-specific risk characterizations exhibit the complexity of flood impacts in North Carolina and can be used to inform future recovery and resiliency efforts.

Recommendations:

Our results identify the distribution of flood-related financial risk of damages to residential properties across multiple groups in North Carolina's Neuse River basin, a significant advance over traditional measures of this risk which are often limited to insured and uninsured damages. Typically, property owners are assumed to directly bear all the risk of uninsured damage to their property, but the risk of these damage-related losses also accrue to mortgage lenders and local governments, while the risk of insured damages is borne by the federal government via the NFIP. Understanding the distribution of this risk provides more useful information for mitigating and managing the financial risk of floods and promoting resilience in the wake of these events. The recommendations described below are enabled by this more highly resolved information on who holds this risk.

Across the Neuse basin, property owners retained 44% of the flood-related financial risk, the majority due to directly to flood damages, with the remainder coming about as a result of reductions in

property value following a flood event. Given the very low levels of flood insurance uptake across the basin, there is a significant opportunity to transfer some of this property owner risk to the federal government by encouraging more owners to purchase this insurance via the NFIP. This will require some effort from the state as flood insurance coverage is already required of properties purchased within a FEMA-designated Special Flood Hazard Area (SFHA) with the help of a federally insured mortgage (i.e., most mortgages). Even with these requirements, however, flood insurance policies only have an average tenure of 2-4 years, despite an average mortgage loan period of 30 years (Michel-Kerjan, Lemoyne de Forges, and Kunreuther 2012). By both enforcing existing rules and providing additional incentives to increase flood insurance uptake by property owners most at risk (i.e. those in the SFHA) considerable risk could be transferred from property owners, as well as lenders and local governments, to the federal government Even greater levels of risk transfer to the federal government could come by encouraging those most at risk of flooding, but outside of the designated SFHAs, from purchasing insurance via the NFIP,, as flood insurance uptake in these areas is even lower than in the SFHA. This would be particularly effective in urban and coastal areas that have a history of flooding, but are not within the mapped SFHA (Association of State Floodplain Managers 2020; Galloway et al. 2018; National Academies of Sciences, Engineering 2019).

Increased enforcement of policies that make purchasing flood insurance the default when deemed required, such as keeping flood insurance in escrow, would increase insurance coverage within the SFHA (Kousky et al. 2020). Multi-year insurance contracts are another proposed solution that are projected to increase coverage (Kunreuther and Michel-Kerjan 2010) and satisfy property owners by locking in coverage at an acceptable price for longer periods (Kleindorfer, Kunreuther, and Ou-Yang 2012). Finally, subsidizing flood insurance premiums in at-risk areas would increase coverage for those unable to pay premiums out of pocket and would contribute to not only reducing the risk to property owners, but also to lenders and local governments. If calibrated properly, these incentives could provide

a positive return on investment to the state, as some financial risk would be shifted to the federal government via payouts of insurance claims and would provide more immediate relief to improve financial resilience in communities that have experienced flooding .

Mortgage lenders hold just under 10% of the basin's flood-related financial risk. The distribution of this risk between national lenders and local lenders will clearly be of importance to efforts to promote financial resilience in the basin, as local banks are an important source of lending to property owners seeking the resources to repair damages. Distinguishing between local and national lenders cannot, however, be determined with existing data, but will be the subject of future investigation. Nonetheless, understanding the potential losses accruing to lenders remains necessary to predict potential changes to community borrowing capacity and stability of local financial institutions.

To protect these parties, post-disaster relief could include policies that help to break the cycle of foreclosed properties, including state-administered individual assistance, mortgage relief packages, or post-disaster foreclosure moratoriums. For example, after Hurricane Sandy hit New York, FEMA and the Department of Housing and Urban Development (HUD) collaborated to provide rental assistance to households temporarily displaced by flood damages to their primary residences to ease short-term financial stress ((IOM) 2015); mortgage lenders also coordinated foreclosure moratorium policies and allowed loan modifications to reduce confusion and financial burden for affected property owners (Hurricane Sandy Rebuilding Task Force 2013). The coordination of these programs was facilitated by the Hurricane Sandy Rebuilding Task Force and is recommended for future disaster planning as well. An analysis of mortgages at risk of default (those with an LTV > 1), as performed in this work, could aid in providing more targeted outreach for post-disaster policies. Further research into the ability of mortgage lenders (both local and national), to absorb losses from flood events is recommended to prepare these institutions to survive these events and continue to provide borrowing resources to their communities in the post-event environment.

Local governments hold 22.9% of the financial risk of flooding in the Neuse basin experienced as a result of Hurricane Florence. First, any action that reduces the flood risk of property owners (e.g., increased uptake of flood insurance) will reduce the probability of local governments ultimately assuming this risk. Additionally, local governments may be able to prevent future flood impacts through alternative zoning rules. Requiring and supporting structural mitigation efforts, such as home elevations, should provide higher levels of protection for property owners already residing in the floodplain, reducing displacement, and encouraging safe neighborhood growth. If development continues in flood prone areas, those exposed to the related financial risk continues to grow; if flooded properties are repurposed and resold without both appropriate mitigation efforts made to the structure and disclosure of flood risk to the new property owner, the pool of property owners at risk is simply refreshed, and mortgage lenders and local governments do not gain any protection. Limiting development in current and future floodplains in North Carolina is one way to decrease the exposure to flood events and the potential of property owner financial risk being passed along to local government through abandoned properties. To assess total financial risk accruing to local governments, future consideration should also be given to the losses arising from reductions in the property tax base due to lower post-event property values, damages to local infrastructure, business disruptions, and the potential long-term effects of blight.

As the results presented from this analysis are specific in space and time, they should not be used as predictive of future impacts; continued work, however, may be able to diagnose appropriate areas for specific interventions.

Implementation Actions

1. Flood insurance, essentially all of which is provided by the federal government via the NFIP, is the primary tool for managing financial risk of flood-related damages for property owners. Managing risk at this level also provides ancillary benefits to reduce risk for lenders and local governments, improving resilience of the entire community. Nonetheless, flood insurance uptake in North Carolina remains very low. The state should target communities at risk to encourage insurance uptake through both education and provision of incentives, such as funding to assist property owners in paying NFIP premiums to cover future damages. The analysis described in this work can inform which counties, neighborhoods, or even individual properties should be targeted to impact the areas most at risk, allowing for a more effective use of state funds.

(Priority: High, 1-2 years)

2. Regardless of any achievable increase in flood insurance uptake, uninsured damages continue to be a reality in North Carolina. The state should initiate renewed efforts to develop pre-disaster mitigation plans via a "portfolio" approach that includes multiple strategies, including infrastructure (e.g., flood control, property elevation), buyouts of at-risk properties, zoning policy and financial instruments (e.g., flood insurance, disaster-based reinsurance). This planning process will benefit significantly from more highly resolved estimates of flood-related financial risk, including who bears the risk and where they are located.

(Priority: High, 1-2 years)

3. The impacts of severe flood events on property value and the ability of property owners to pay their mortgages represents a longstanding, but thus far unquantified source of risk to both lenders and local governments. The levels of home abandonment and neighborhood blight in New Orleans following Hurricane Katrina serve as a stark warning of the devastating and long-term community impacts that can result. Any flood-related uptick in mortgage defaults can reduce the ability of local lenders to provide capital for repairs to damaged properties, lowering community post-flood resilience. A rigorous and detailed assessment of neighborhoods at highest risk of flood-related mortgage default should be conducted to identify which areas and lenders are most threated, and to inform actions designed to mitigate this risk (e.g., property buyouts, lines of credit to vulnerable banks).

(Priority: Medium, 3-5 years)

4. Development in floodplains and reselling of flood damaged properties continues to expose property owners, mortgage lenders, and local governments to financial risk from future flood events. Planning efforts that reduce development in areas most at risk of flooding (e.g., flood plains) that decrease the financial risk of these events should be pursued at the local, county, and state level.

(Priority: Medium, 3-5 years)

Accurately estimating damages post-disaster is difficult to quantify, and related data is often scattered and disorganized. Nonetheless, this information is critical to the development and execution of post-disaster recovery efforts. The more highly resolved these estimates are with respect to who has been impacted and how severely, the more targeted and effective recovery efforts will be. The state should

therefore increase efforts to identify areas and parties at greatest risk from flooding and set up systems to collect and rapidly disseminate post-flood damage information to inform targeted resiliency efforts.

(Priority: Medium, 3-5 years)

6. Many parts of North Carolina including urban areas and communities in some western parts of the state are largely unfamiliar with flood events but may be at greater risk in the future. A more comprehensive assessment of statewide flood risk and the attendant financial risk would give state agencies a better understanding of risk and improved ability to assess the feasibility of a range of risk management actions. . Additionally, greater specificity with respect to who holds flood-related financial risk should be identified to inform preparation and mitigation strategies.

(Priority: Low, 5-10 years)

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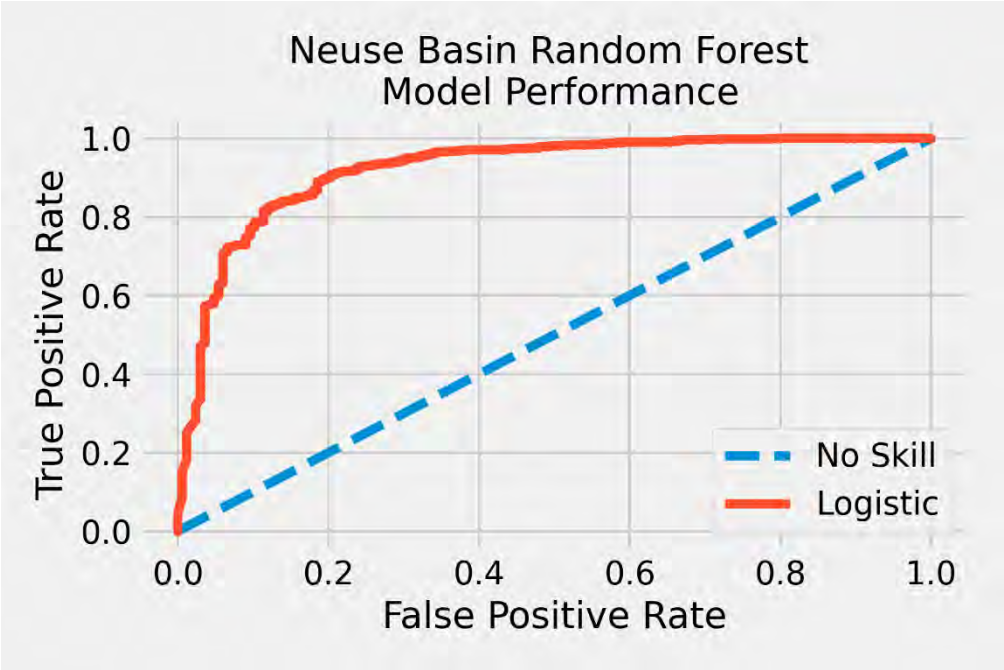
APPENDIX

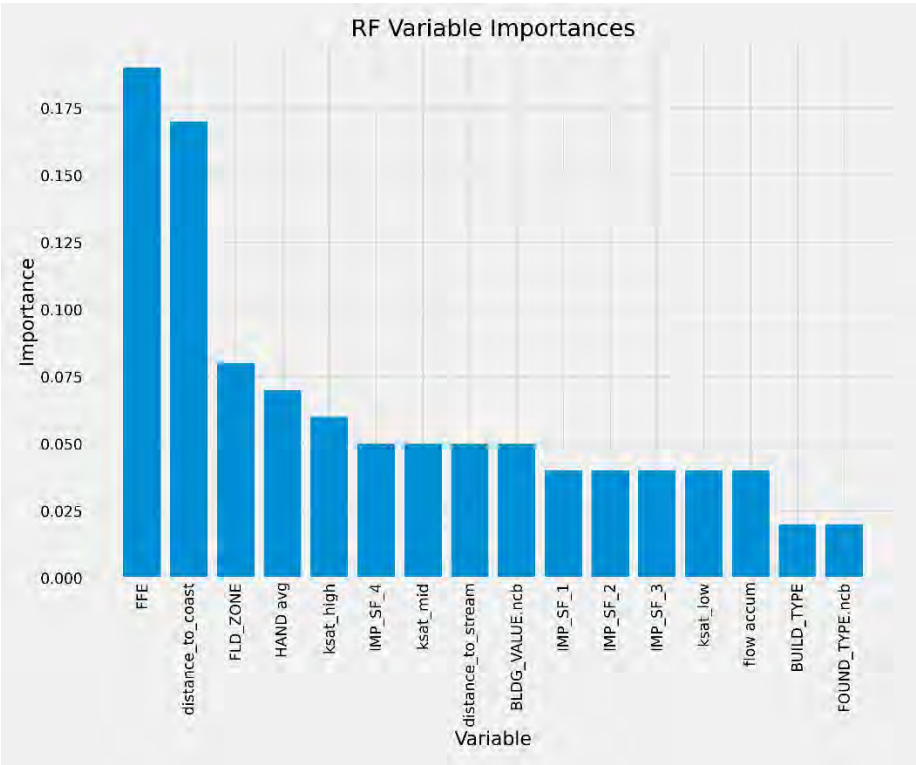
Table 3: Hurricane Florence flood risk profiles in counties contained by the Neuse watershed

Area	NFIP ($MM)	Property owners ($MM)	Lenders/Banks ($MM)	Local governments ($MM)	Total Risk ($MM)
Carteret	6.32	5.36	2.70	11.30	25.68
Craven	205.93	343.36	80.42	91.02	720.72
Durham	0.77	3.91	0.95	0.00	5.63
Greene	0.00	0.02	0.00	0.00	0.02
Johnston	0.07	0.40	0.04	0.58	1.08
Jones	18.54	13.72	3.53	21.92	57.70
Lenoir	25.58	16.08	5.18	1.34	48.18
Pamlico	63.21	175.92	17.45	166.94	423.53
Pitt	0.00	0.01	0.10	0.06	0.16
Wayne	0.51	0.92	0.12	0.98	2.53
Wilson	0.03	0.28	0.04	0.36	0.71
Neuse (basin-wide)	320.95	559.98	110.52	294.50	1285.95

Random Forest classification model ROC Curve:



Random Forest model variable importances:



Variable names key:

FFE: First floor elevation
Distance_to_coast, _stream: distances to coast/stream
FLD_ZONE: NFIP-designated flood zone
HAND_avg: parcel-averaged height above nearest drainage (HAND)
IMP_SF (4): impervious surface coverage in areas surrounding parcel.
Ksat(3; high, mid, low): hydraulic soil conductivity of parcel
BLDG_VALUE: tax-assessed building value
BUILD_TYPE: building materials.
FOUND_TYPE: foundation materials/type.

References

(IOM), Institute of Medicine. 2015. "Healthy, Resilient, and Sustainable Communities after Disasters: Strategies, Opportunities, and Planning for Recovery." In National Academies Press (US), 403–16. https://www.ncbi.nlm.nih.gov/books/NBK316535/ (April 30, 2021).

Association of State Floodplain Managers. 2020. *Urban Flood Hazards: Challenges and Opportunities*. Madison, WI.

Band, Shahab S. et al. 2020. "Flash Flood Susceptibility Modeling Using New Approaches of Hybrid and Ensemble Tree-Based Machine Learning Algorithms." *Remote Sensing* 12(21): 3568. https://www.mdpi.com/2072-4292/12/21/3568 (April 30, 2021).

Bin, Okmyung, and Stephen Polasky. 2004. "Effects of Flood Hazards on Property Values: Evidence before and after Hurricane Floyd." *Land Economics* 80(4): 490–500.

Boyle, M., and K. Kiel. 2020. "A Survey of House Price Hedonic Studies of the Impact of Environmental Externalities." *Journal of Real Estate Literature* 9(2): 117–44. https://www.tandfonline.com/doi/abs/10.1080/10835547.2001.12090098.

Carter, L et al. 2018. "Impacts, Risks and Adaptation in the United States: Fourth National Climate Assessment, Southeast." : 743–808. https://nca2018.globalchange.gov/downloads/NCA4_Ch19_Southeast_Full.pdf (April 6, 2021).

Clowers, A. Nicole. 2010. *Mortgage Foreclosures: Additional Mortgage Servicer Actions Could Help Reduce the Frequency and Impact of Abandoned Foreclosures*.

Colman, Zack. 2020. "How Climate Change Could Spark the next Home Mortgage Disaster." *Politico*. https://www.politico.com/news/2020/11/30/climate-change-mortgage-housing-environment-433721 (December 9, 2020).

CoreLogic. 2018. "The Aftermath of Hurricane Florence Is Estimated to Have Caused Between $20 Billion and $30 Billion in Flood and Wind Losses, CoreLogic Analysis Shows." https://www.corelogic.com/news/the-aftermath-of-hurricane-florence-is-estimated-to-have-caused-between-20-billion-and-30-billion-in-flood-and-wind-losses-cor.aspx (April 29, 2021).

Demographer, NC. 2021. "Projected Population Change in North Carolina Counties." *Office of State Budget and Management*. https://files.nc.gov/ncosbm/demog/countygrowth_2020.html (April 8, 2021).

FEMA. 2020. "City of New Bern to Receive More Than $1.9 Million for Electrical Repairs ." *FEMA NR 220*. https://www.fema.gov/press-release/20210318/city-new-bern-receive-more-19-million-electrical-repairs (April 16, 2021).

FFIEC. 2020. "Dynamic National Loan-Level Dataset." *Federal Financial Institutions Evaluation Council*. https://ffiec.cfpb.gov/data-publication/dynamic-national-loan-level-dataset.

Freni, G., G. La Loggia, and V. Notaro. 2010. "Uncertainty in Urban Flood Damage Assessment Due to Urban Drainage Modelling and Depth-Damage Curve Estimation." *Water Science and Technology* 61(12): 2979–93.

Gallagher, Justin, and Daniel Hartley. 2017. "Household Finance after a Natural Disaster: The Case of

Hurricane Katrina †." *American Economic Journal: Economic Policy* 9(3): 199–228. https://doi.org/10.1257/pol.20140273 (April 15, 2021).

Galloway, Gerald et al. 2018. *The Growing Threat of Urban Flooding: A National Challenge*.

Guyton, Lori. 2017. "CoreLogic Analysis Estimates Total Residential Insured and Uninsured Flood Loss for Hurricane Harvey Between $25 Billion and $37 Billion." *CoreLogic*. https://investor.corelogic.com/pressreleases/corelogic-analysis-estimates-total-residential-insured-and-uninsured-flood-loss (April 18, 2021).

He, Haibo, and Yunqian Ma. 2013. *Imbalanced Learning: Foundations, Algorithms, and Applications* . illustrated. John Wiley & Sons. https://books.google.com/books?id=CVHx-Gp9jzUC&lr=&source=gbs_navlinks_s (April 25, 2021).

Howard, L.S. 2019. "Hurricane Florence Demonstrates Perils of Being Underinsured/Uninsured, Says RMS." *Insurance Journal*. https://www.insurancejournal.com/news/international/2019/01/24/515650.htm (April 16, 2021).

Hurricane Sandy Rebuilding Task Force. 2013. *HURRICANE SANDY REBUILDING STRATEGY : Stronger Communities, A Resilient Region Hurricane Sandy Rebuilding Task Force*. https://www.hud.gov/sites/documents/HSREBUILDINGSTRATEGY.PDF (April 30, 2021).

Insurance Information Institute. 2020. "Spotlight on: Flood Insurance ." https://www.iii.org/article/spotlight-on-flood-insurance (April 25, 2021).

Keenan, Jesse M., and Jacob T. Bradt. 2020. "Underwaterwriting: From Theory to Empiricism in Regional Mortgage Markets in the U.S." *Climatic Change* 162(4): 2043–67.

Kim, Hyun Il, and Byung Hyun Kim. 2020. "Flood Hazard Rating Prediction for Urban Areas Using Random Forest and LSTM." *KSCE Journal of Civil Engineering* 24(12): 3884–96. www.springer.com/12205.

Kleindorfer, Paul R., Howard Kunreuther, and Chieh Ou-Yang. 2012. "Single-Year and Multi-Year Insurance Policies in a Competitive Market." *Journal of Risk and Uncertainty* 45(1): 51–78. http://repository.upenn.edu/oid_papers (April 30, 2021).

Knighton, James et al. 2020. "Predicting Flood Insurance Claims with Hydrologic and Socioeconomic Demographics via Machine Learning: Exploring the Roles of Topography, Minority Populations, and Political Dissimilarity." *Journal of Environmental Management* 272.

Kousky, Carolyn. 2010. "Learning from Extreme Events: Risk Perceptions after the Flood." *Land Economics* 86(3): 395–422.

Kousky, Carolyn, Howard Kunreuther, Michael LaCour-Little, and Susan Wachter. 2020. "Flood Risk and the U.S. Housing Market." *Journal of Housing Research* 29(sup1): S3–24. https://www.tandfonline.com/doi/full/10.1080/10527001.2020.1836915 (April 16, 2021).

Kousky, Carolyn, Mark Palim, and Ying Pan. 2020. "Flood Damage and Mortgage Credit Risk: A Case Study of Hurricane Harvey." *Journal of Housing Research* 29(sup1): S86–120. https://doi.org/10.1080/10527001.2020.1840131.

Kunreuther, Howard C., and Erwann O. Michel-Kerjan. 2010. 2 The Economics of Natural and Unnatural Disasters *Market and Government Failure in Insuring and Mitigating Natural Catastrophes: How Long-Term Contracts Can Help*.

Le, Nhu D., and James V. Zidek. 2006. *Statistical Analysis of Environmental Space-Time Processes*. New York City, New York: Springer Science+Business Media, Inc.

Marlett, David C, Lorilee A Medders, and Catherine A Lattimore. 2020. *An Evaluation of the North Carolina Rate Bureau's Residential Flood Insurance Program* .

McAlpine, S, and J Porter. 2018. "Estimating Recent Local Impacts of Sea-Level Rise on Current Real-Estate Losses: A Housing Market Case Study in Miami-Dade, Florida." *Population Research and Policy Review* (37): 871–95.

Merz, B., H. Kreibich, A. Thieken, and R. Schmidtke. 2004. "Estimation Uncertainty of Direct Monetary Flood Damage to Buildings." *Natural Hazards and Earth System Science* 4(1): 153–63.

Michel-Kerjan, Erwann, Sabine Lemoyne de Forges, and Howard Kunreuther. 2012. "Policy Tenure Under the U.S. National Flood Insurance Program (NFIP)." *Risk Analysis* 32(4): 644–58. http://doi.wiley.com/10.1111/j.1539-6924.2011.01671.x.

Mobley, William et al. 2020. "Quantification of Continuous Flood Hazard Using Random Forrest Classification and Flood Insurance Claims at Large Spatial Scales: A Pilot Study in Southeast Texas." *Natural Hazards and Earth System Sciences Discussions*: 1–22.

Mobley, William, Antonia Sebastian, Wesley Highfield, and Samuel D. Brody. 2019. "Estimating Flood Extent during Hurricane Harvey Using Maximum Entropy to Build a Hazard Distribution Model." *Journal of Flood Risk Management* 12(S1).

National Academies of Sciences, Engineering, and Medicine 2019. 2019. Framing the Challenge of Urban Flooding in the United States *Framing the Challenge of Urban Flooding in the United States*. Washington, D.C.: The National Academies Press.

NOAA. 2020. "U.S. Billion-Dollar Weather and Climate Disasters, 1980 - Present." *National Centers for Environmental Information*. https://accession.nodc.noaa.gov/0209268 (April 5, 2021).

Nofal, Omar M., and John W. van de Lindt. 2020. "Understanding Flood Risk in the Context of Community Resilience Modeling for the Built Environment: Research Needs and Trends." *Sustainable and Resilient Infrastructure*.

North Carolina Department of Public Safety. 2018. "Hurricane Florence Preliminary Impact Summary." https://www.ncdps.gov/florence.

Pace, R.K., R. Barry, and C.F. Sirmans. 1998. "Spatial Statistics and Real Estate." *Journal of Real Estate Finance and Economics* 17(1): 5–13. https://link.springer.com/article/10.1023/A:1007783811760.

RMS. 2018. "RMS Estimates Insured Losses From Hurricane Florence Will Be Between USD $2.8 Billion and USD $5.0 Billion ." https://www.rms.com/newsroom/press-releases/press-detail/2018-09-24/rms-estimates-insured-losses-from-hurricane-florence-will-be-between-usd-28-billion-and-usd-50-billion (April 29, 2021).

Smith, T.K., and J. Huang. 1995. "Can Markets Value Air Quality? A Meta-Analysis of Hedonic Property Value Models." *Journal of Political Economy* 103(1): 209–27. https://www.jstor.org/stable/pdf/2138724.pdf?casa_token=1JjgEoUex8QAAAAA:UWKKt2tDro8JHiap-5vYWdnJYcd-LGV84gvgXFwRK9lPsRRzZWsAyvqCTJ3qI3PKz4Unr83q0jmwi6RXd_y3FMo75RjvAUj77KiJNqaMe0P35xVYaves.

Sumell, A. 2009. “The Determinants of Foreclosed Property Values: Evidence from Inner-City Cleveland.” *Journal of Housing Research* 18(1): 45–61. https://www.jstor.org/stable/24861467?seq=1.

Tippett, Rebecca. 2020. “North Carolina on Track to Surpass 10.6 Million by 2020, Gain in the House | Carolina Demography.” *Carolina Demography*. https://www.ncdemography.org/2020/01/16/north-carolina-on-track-to-surpass-10-6-million-by-2020-gain-in-the-house/ (April 8, 2021).

Waller, Lance A., and Carol Gotway. 2004. *Applied Spatial Statistics for Public Health Data*. John Wiley & Sons. www.copyright.com.

Wing, Oliver E.J., Nicholas Pinter, Paul D. Bates, and Carolyn Kousky. 2020. “New Insights into US Flood Vulnerability Revealed from Flood Insurance Big Data.” *Nature Communications* 11(1). /pmc/articles/PMC7081335/ (April 5, 2021).

Data Sources

[i] Dombrowski, T., Ratnadiwakara, D., & Jr., V. C. S. (2020). The FEMA NFIP’s Redacted Policies and Redacted Claims Datasets. *Journal of Real Estate Literature*, *28*(2), 190–212. https://doi.org/10.1080/09277544.2021.1876435

[ii] North Carolina Department of Information Technology. (2021). *NC OneMap Geospatial Portal*. Government Data Analytics Center, Center for Geographic Information and Analysis. https://www.nconemap.gov.

[iii] Jin, S., Homer, C., Yang, L., Danielson, P., Dewitz, J., Li, C., Zhu, Z., Xian, G., & Howard, D. (2019). Overall Methodology Design for the United States National Land Cover Database 2016 Products. *Remote Sensing*, *11*(24). https://doi.org/10.3390/rs11242971

[iv] Buto, S. G., & Anderson, R. D. (2020). NHDPlus High Resolution (NHDPlus HR)---A hydrography framework for the Nation. In *USGS*. https://doi.org/10.3133/fs20203033

[v] Liu, Y. Y., Tarboton, D. G., & Maidment, D. R. (2020). Height Above Nearest Drainage (HAND) and Hydraulic Property Table for CONUS - Version 0.2.1. *Oak Ridge Leadership Computing Facility*, *20200601*. https://doi.org/10.13139/ORNLNCCS/1630903

[vi] Soil Survey Staff, N. R. C. S. (n.d.). *Soil Survey Geographic (SSURGO) Database.* United States Department of Agriculture. Retrieved January 3, 2021, from https://sdmdataaccess.sc.egov.usda.gov.