Earth's Future

Supporting Information for

Systemic Financial Risk Arising from Residential Flood Losses

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Introduction

This Supporting Information contains five additional text sections, S1-S5, five additional figures, S1-S5 and five additional tables, S1, S3-S6. Figures S1-S5 support Section 2.2.4 of the main text. Table S1 supports section 2.1 of the main text, while Tables S2-S7 support section 3 of the main text. Table S2 and S7 are included as separate files.

Text S1. Federal Disaster Relief

Funding to support recovery from natural disasters such as floods is provided by several federal agencies, including the Federal Emergency Management Agency (FEMA). Within FEMA, the Federal Insurance and Mitigation Administration (FIMA) collects flood insurance premium payments from participating individuals and administers post-flood NFIP insurance payouts up to $350,000 for residential flood damages ($250k structure; $100k contents). Active NFIP insurance policies are required for properties with a federally backed mortgage (insured by a federal government agency) located in the FEMA Special Flood Hazard Area (SFHA), but studies of insurance uptake suggest that compliance is low (Kousky, 2011; Michel-Kerjan et al., 2012). Nationwide, participation in the NFIP by single family residential structures located within the SFHA is estimated to be 48% (Bradt et al., 2021) with significant regional variation, including both higher rates of purchase (61%) in the southern United States and lower rates (22%) in the Midwest (Dixon et al., 2006). In a study conducted by the Department of Housing and Urban Development, rates of insurance purchase among North Carolina properties in 2018 with federally backed mortgages within the SFHA was estimated as either 22% or 50%, depending on methods of property geolocation (HUD, 2020). Flood insurance is also available to properties outside the SFHA, yet the rate of voluntary insurance purchase is low, a trend that has been explain by individuals underestimating their flood risk, the net benefit of purchasing flood insurance, and the federal government's ability to provide support after a flood event (Kousky et al., 2020; Kunreuther, 2006; Petrolia et al., 2013; Shao et al., 2017). However, flooding outside of the SFHA can account for a large fraction of the total damage (Blessing et al., 2017; Brody et al., 2013; Highfield et al., 2013).

The NFIP also faces solvency issues, with a current debt to the United States Treasury of $20.25 billion (Congressional Research Service, 2021a) often attributed to outdated flood risk maps, grandfathered premiums, and non-actuarial pricing of risk (Kousky, 2017). Historically, private flood insurance provision has been minimal, and so threats to the financial stability and political viability of the NFIP jeopardize provision of flood insurance as a public good nationwide and its use as a protective recovery mechanism from flood events (Knowles & Kunreuther, 2014; Kousky et al., 2018). Expansion of coverage through the NFIP, for example through updated compliance requirements or more current flood risk maps, could reduce the proportion of damage that is uninsured in the wake of a flood event (Government Accountability Office, 2017, 2021). However, changes to the NFIP are politically contentious (Flavelle & Cochrane, 2021; Knowles & Kunreuther, 2014). The potential impact of current proposed changes on reduction of uninsured damage is undetermined, especially as the changes focus on modifying rate structures to actuarially reflect risk, rather than changes in eligibility or mandatory compliance that would increase penetration (Congressional Research Service, 2021b).

Not all disaster recovery funding available to property owners is included in this model framework. For uninsured properties in a presidentially designated disaster area, Individual Assistance (IA) grants may be available to address damage, but grants are "intended to supplement, but not substitute, existing insurance coverage" (FEMA, 2019). Eligibility for these funds is contingent on other forms of disaster aid not meeting disaster-caused needs, and the maximum IA grant award is $36,000 (FEMA, 2021a). These grant programs are excluded from this analysis as they are not uniformly applied, and their scale is not influential for individual property recovery decisions, as they cannot cover replacement of a heavily damaged residence (Lindsay, 2017). For instance, from 2016-2018, 4.4 million individuals (including property owners and renters) applied for IA grants and only 2 million were found eligible. Of this group, the average IA awarded by FEMA to property owners experiencing damages was $4,200 (Government Accountability Office, 2020a).

In wake of a presidentially declared disaster, the Small Business Administration (SBA) provides disaster home loans up to $200,000 (Lindsay & Webster, 2019). Mortgage refinance loans from private lenders typically cannot increase mortgage balances above 80% of the property market value (Caplin et al., 1997), but SBA disaster lending program has no such collateral restrictions for property owners with insufficient equity. Other advantages to the loan program include an 18-month grace period before repayment, low interest rates, long loan terms, and ability to increase loan amount to make structural improvements (FEMA, 2021b). However, if collateral via equity is available, property owners may be required to pledge that collateral to secure the loan, and there are other restrictions such as credit history and ability to pay can cause rejection of SBA loan applications (Lindsay & Webster, 2019). In 2017, following Hurricanes Harvey, Irma, and Maria, about 49% of SBA disaster loan applications were approved (Government Accountability Office, 2020b); these rejections may exacerbate preexisting financial inequalities, impacting post-flood recovery success (Billings et al., 2019).

Other forms of disaster relief and mitigation funds, such as community-block development disaster recovery grants (CDBG) and public assistance (PA) grants have long lead times, are intended for community-level interventions and recovery and are intended for long-term recovery needs (FEMA, 2020; HUD, n.d.). As this analysis focuses on the risks present to individual properties immediately following a flood event, these funding streams are less applicable in the determination of flood-related financial risk.

Text S2. Data Collection and Variable Creation

The models within the framework use several unique datasets as inputs. Data source, resolution, and use within the modeling framework are described in Table S1, with model designations following the numbering in Figure 3. Natural environment data describe hydrologic characteristics. Property data includes variables that inform both property values (e.g., structure square footage, parcel square footage, and year built) and vulnerability to flood impacts (e.g., first floor elevation). Natural environment data are used in the random forest model (I), while property data are used in both the random forest (I) and the spatial interpolation model (II). Financial data include NFIP policy and claims (used in model I), property sales (used in models II and III), and mortgage loan originations (used in models II and III). Details regarding variable creation details are below Table S1.

Table S1. Variables used within the flood-related financial risk model framework

Variable Name	**Source**	**Spatial Resolution**	**Model Usage**
First floor elevation	NC OneMap	Property	I
FEMA-designated flood zone	NC OneMap	Property	I
Surrounding impervious surfaces	National Land Cover Database, 2016	30mx30m raster	I
Distance to nearest stream	National Hydrography Dataset	Property	I
Distance to coast	National Hydrography Dataset	Property	I
Maximum overland flow accumulation	National Hydrography Dataset	10m x 10m raster	I
Hydraulic soil conductivity (Ksat)	USGS SSURGO	Variable polygons	I
Foundation type	NC OneMap	Property	I
Tax -assessed value	NC OneMap	Property	I
Year built	NC OneMap	Property	I, II
Structure square footage	NC OneMap	Property	I, II
Parcel square footage	NC OneMap	Property	II
Distance to county courthouse	USGS National Map Corps	Property	II
Incorporated status	U.S. Census Bureau	Property	II
NFIP policies and claims	OpenFEMA	Property	I
Property sales	ATTOM	Property	II, III
Mortgage loan originations	FFIEC	Census tract	II, III
Mortgage repayments, delinquencies	Fannie Mae	Zip code	

Parcel-level variables were created to aggregate building characteristics collocated on a single parcel and to tie environmental characteristics to the parcel itself. For the random forest damage estimation model, 19 variables (7 property, 12 environmental) were originally created and used in the model before pruning to those included in Table S1.

Using the ATTOM property sale data, the geodesic distance from parcel midpoint to county courthouse was found. An incorporation status variable was also made using census data, where parcels with C1, C5, and C9 codes were designated as incorporated, and all the rest unincorporated. Property value data was clipped to the eastern NC region, and rows without an identifier, geometry, date of transfer, property value were removed; additionally, rows with property values less than $1,000 were removed. To only include residential sales, fields with use codes containing "COMM" were removed.

Using buildings data from NC OneMap, duplicated rows were dropped and rows with null building IDs were removed. Buildings found to geospatially intersect with multiple parcels, were assigned to one of the intersecting parcels randomly so that each building is associated with a single parcel. Then, duplicated buildings on a single parcel were identified, and scaled to the parcel level in different ways depending on the attribute. Most of the attributes (i.e., IDs, codes, qualitative attributes such as foundation type, binary variables) were scaled to parcel level by choosing by the most frequent occurrence then randomly selecting between the most frequent occurrences in the case of a tie. For building value and square footage fields the sum of the values was taken. The maximum of the values was taken for year built and highest adjacent grade (HAG), and minimum for lowest adjacent grade (LAG) and first floor elevation (FFE). The buildings were then filtered by use codes, keeping residential codes only (1245,1250,1255,1580,1585,1590,2245,2250,2255,2580,2585,2590,3245,3250,3255,4245,4250,4255,5245,5250,5255,5580, or 5585), and joined to the parcel shapefiles.

If a parcel was within the SFHA, the FFE was originally derived by the state using either laser inclinometer or terrestrial LiDAR. However, in communications with state officials responsible for creating the dataset, they explained that parcels outside of the SFHA used a derived FFE of nearby LAG plus 2.5 feet for freeboard. For this analysis, we estimate the FFE outside the SFHA as this derived FFE minus 2.5 feet of freeboard. Status within a FEMA flood zone was included in NC OneMap datasets; for this analysis, all A zones and the VE zone were considered within the floodplain.

The surrounding impervious surfaces were measured Using land use land cover data from the Multi-Resolution Land Characteristics Consortium (MRLC)., The MRLC dataset contains four types of developed land cover codes, representing land with impervious surfaces covering 10%, 35%, 65%, and 90% of the area (all other land cover codes are assumed to have 0% impervious surface coverage). The nearby impervious surface coverage is calculated for each parcel at four different spatial ranges. Starting with the parcel centroid at the center, the MRLC raster data is clipped using four individual circles with radii of 300 m, 825 m, 2.25 km, and 6.0 km. The average imperviousness of all the raster cells that fall within each circle provides each grid cell with four unique values of nearby impervious surface coverage.

The soil hydraulic conductivity is calculated at each parcel using the SSURGO soils database. Soil type GIS data were used to place each parcel within a particular SSURGO Hydraulic Soil Group, and the high, low, and representative saturated hydraulic conductivities associated with each group are assigned to the relevant parcels.

The distance of each parcel to the nearest stream and coastline were calculated using GIS data from the USGS National Hydrography Plus High-Resolution vectors dataset (streams) and the NOAA composite shoreline shapefiles. Streams of order 3 – 8 were considered and distances to parcel shapefiles were calculated using the SciPy function ckd_tree.

Overland flow used the United States Geological Survey's National Hydrography Plus High-Resolution Rasters dataset. The raster was clipped by the parcel footprint and both a mean and maximum value were found; only the maximum overland flow was used in the final model.

We tested height above nearest drainage variables using the rasters generated by (Liu et al., 2020) and stored at Oak Ridge National Laboratory. The raster was clipped using the parcel footprint, and a mean value and maximum value across the parcel were stored. Both variables were eliminated during the pruning process.

Text S3. Property Value Modelling Details

To evaluate the accuracy of estimated modelled property values across the entire study region, we calculate the percent error associated with each observed transaction relative to the predicted property value in the previous timestep, such that:

$$PE_{p,t} = \frac{|TV_{p,t} - PV_{p,t-1}|}{\max(TV_{p,t},\ PV_{p,t-1})} \quad \text{(S1.1)}$$

where *PE* = percent error; *TV* = observed transaction value; *PV* = property value estimation; *p* = parcel ID; *t* = timestep

Kriged estimates of property values have significantly smaller percent error than the hedonic estimations of property value alone, illustrating that the spatial/temporal interpolation of property transaction observations increase the ability to predict future transaction values (Figure 6 in the main text). Across the entire study area, 18% of the interpolated property value estimations were within 10% of the subsequent observed transaction values, compared to only 9% of the hedonic estimations. If we expand the error tolerance to 20%, 35% of the interpolated estimates had smaller errors while only 22% of the hedonic estimates did. Over half of the interpolated estimates fell within a 33% error tolerance, and 74% of the estimates fell within a 50% tolerance (compared to 38 and 54%, respectively, of the hedonic estimations). Although there is significant uncertainty in estimates of future property values, these results show that the methods described here to integrate observed transaction values with a hedonic property valuation model provides spatial and temporal resolution to property value estimations that can be used to assess the impact of a discrete flooding event.

Text S4. Mortgage Repayment Modelling Details

Loan-to-value estimations made using the mortgage repayment model can be validated with historical loan repayment data from Fannie Mae's dynamic loan dataset. In the Fannie Mae historical loan repayment dataset, monthly mortgage balances are provided for a small subset of mortgages that are purchased by Fannie Mae and packaged into their mortgage-backed security (MBS) products. Fannie Mae provides historical loan pools for mortgages that were originated as far back as the first quarter of 2000, creating a sample of mortgages that can be used to tract 'snapshots' of the distribution of existing loan-to-value ratios at any point in time. These observations can be used to validate the mortgage repayment model used to estimate loan-to-value ratios immediately before the event of interest (September 2018 for Hurricane Florence) (Figure S1). There are systemic differences between the mortgage originations that are purchased by Fannie Mae and those which are not (Figure S2), so the LTV observations collected by Fannie Mae can only be reasonably compared to modelled loan-to-value ratios in mortgages that were subsequently purchased by Fannie Mae. Also, Fannie Mae historical data does not adjust for changing property values, so our validation compares modelled loan-to-value data without adjusting for changing property values over the course of the loan. The observed distribution has a higher concentration of mortgages at very low loan-to-value ratios than the modelled dataset, but there is general agreement between the distributions.

To validate our predictions of elevated default risk in select areas of the study region (Figure S3), we plotted serious delinquencies (Figure S4) as tracked by Fannie Mae at the 3-digit zip code level in the year following Hurricane Florence. Delinquencies over 90 days rose in the areas most affected by the flood (shaded orange, red, on the figure), showing substantial agreement with the modelled predictions for elevated default risk. The spatial distribution of pre-flood property values (Figure S5) reiterates the importance of these pre-flood financial conditions in determining vulnerability to mortgage default and abandonment, as the median property values in the study area, but particularly in census tracts with high percentages of properties modelled as at risk of these processes, are quite low (<$150K).

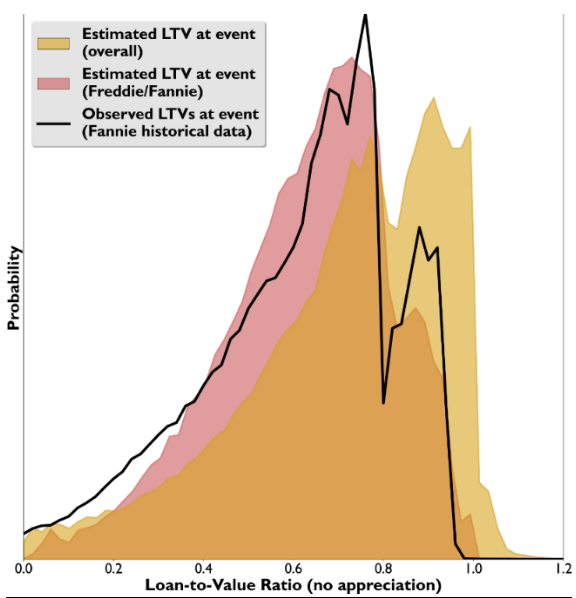

Figure S1. Distributions of modelled versus observed LTV ratios.

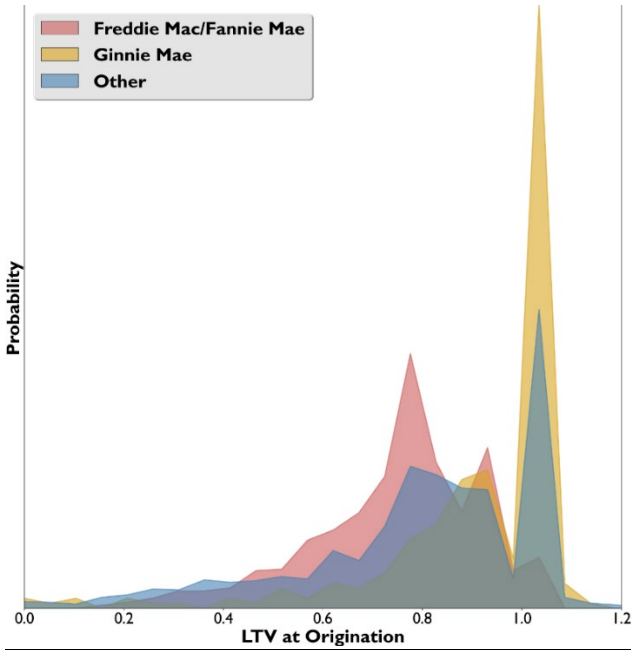

Figure S2. Loan-to-value ratios at origination, by the secondary market purchaser of the loan

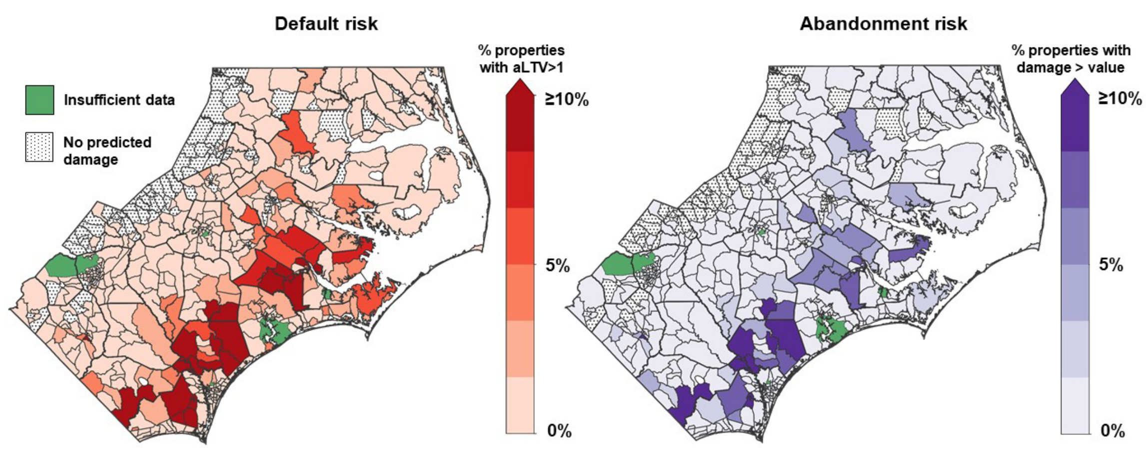

Figure S3. Predicted default risk (aLTV >1), left, and abandonment risk (damage > value), right, at census tracts across the study region after Hurricane Florence

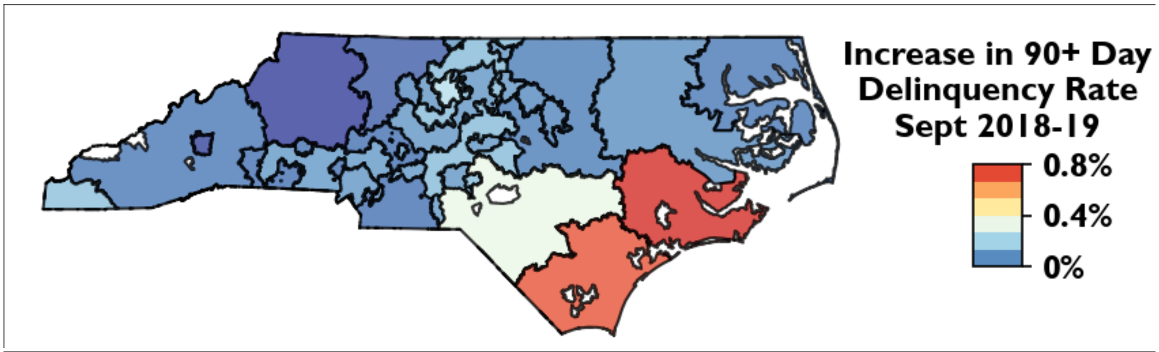

Figure S4. Observed serious delinquency (90+ days) as default risk at 3-digit zip code level

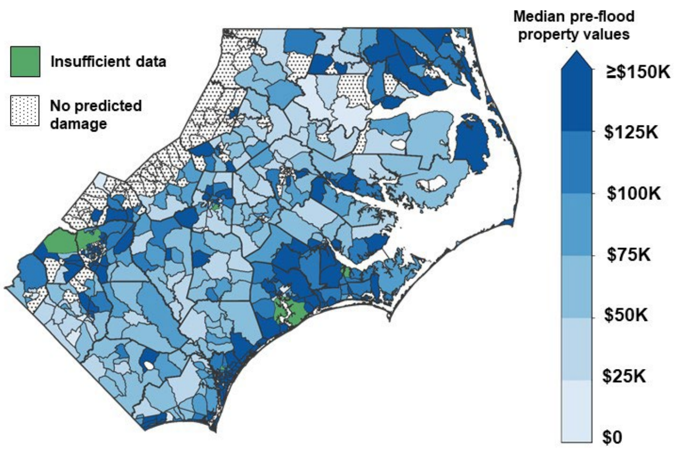

Figure S5. Median pre-flood property values at the census tract level.

Text S5. Additional Results

Results in the main text are presented in larger aggregate scales. Below are results at a finer spatial resolution regarding flood-related balance sheet losses and financial risks at the county scale and across comparative groups.

Table S3. Summary statistics of uninsured damages among comparative groups

Comparative Group	Minimum	Median	95th %	Maximum
Coastal	0.0	19,382.99	75,392.85	188,888.97
Non-coastal	0.0	26,948.52	82,006.97	246,501.95
SFHA	0.0	13,051.69	65,218.19	203,864.84
Non-SFHA	0.0	32,013.49	84,984.14	246,501.95
Incorporated	0.0	15,437.74	58,170.59	165,838.8
Unincorporated	0.0	27,320.98	82,725.37	246,501.95

Table S4. Summary statistics of property value loss among comparative groups

Comparative Group	Minimum	Median	95th %	Maximum
Coastal	0.0	1,128.92	103,687.02	2806,539.81
Non-coastal	0.0	664.78	65,507.89	1,367,116.0
SFHA	0.0	801.26	114,900.61	2,806,539.81
Non-SFHA	0.0	1,034.92	69,691.55	2,463,121.35
Incorporated	0.0	1,570.99	113,011.79	2,806,539.81
Unincorporated	0.0	650.96	85,002.49	2,463,121.35

Table S5. Summary statistics of uninsured damage to pre-flood property ratios among comparative groups

Comparative Group	Minimum	Median	95th %	Maximum
Coastal	0	.18	2.49	9.97
Non-coastal	0	.50	2.84	9.9
SFHA	0	.09	2.02	9.86
Non-SFHA	0	.51	3.21	9.97
Incorporated	0	.12	1.72	9.86
Unincorporated	0	.37	3.08	9.97

Table S6. Summary statistics of property value loss as a percentage of pre-flood property value among damaged properties that lost value

Comparative Group	Minimum	Median	95th %	Maximum
Coastal	0	.21	.60	.99
Non-coastal	0	.19	.61	.94
SFHA	0	.21	.61	.99
Non-SFHA	0	.20	.60	.95
Incorporated	0	.19	.58	.95
Unincorporated	0	.21	.62	.99

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